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Early Warning and Crop Condition Assessment

November 1982

Final Report

DEVELOPMENT OF AN EARLY WARNING SYSTEM OF CROP MOISTURE CONDITIONS USING PASSIVE MICROWAVE

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16. Abstract Over large cropland areas, qualitative states of crop moisture, and to some extent, quantitative estimates can be determined from existing satellite remote sensors operating in passive microwave frequencies. These estimates are essential for large scale monitoring of crops such as winter wheat. Based on demonstrated relationships between microwave brightness temperatures and precipitation histories, this research has the objectives of development of an early warning screening program for moisture deficiencies or excesses at planting time and critical growth periods, and the development of an index of accumulated crop moisture and plant stress.					
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FINAL REPORT

DEVELOPMENT OF AN EARLY WARNING SYSTEM OF CROP
MOISTURE CONDITIONS USING PASSIVE MICROWAVE

by

Marshall J. McFarland
Paul H. Harder, II

This report describes activity carried out in support of the
Early Warning Crop Condition Assessment Project in AgRISTARS

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College Station, Texas 77843

November 1982

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ABSTRACT

Emissivities were calculated from the Nimbus 5 Electrically Scanning Microwave Radiometer (ESMR) over 25 km grid cells for the period September 1973 through May 1975 for the southern Great Plains including the western two-thirds of Kansas and Oklahoma and northwest Texas. These emissivities, normalized for seasonal temperature changes, were in excellent agreement with theory and measurements made from aircraft and truck sensors at the 1.55 cm wavelength of ESMR. These emissivities were related to crop moisture conditions of the winter wheat in the major wheat producing counties of the three states. High correlations were noted between emissivity and an antecedent precipitation index (API) used to infer soil moisture for periods when the soils were essentially bare. The emissivities from ESMR were related through API and actual crop condition reports to progress of fall planting, adequacy of crop moisture for stand establishment, and periods of excessive moisture that necessitated replanting. Periods of prolonged frozen soil in the winter were observable at several grid points. The average emissivities of the canopy/soil surface during the maximum canopy development times in the spring showed a good agreement with moisture stress inferred from rainfall and yield data. Discriminant analyses of the emissivities for both rainfall and API produced probabilistic relationships of total rainfall and maximum rainfall for given sequences of spacecraft for early warning of crop conditions is strongly supported by the research.

DEVELOPMENT OF AN EARLY WARNING SYSTEM OF CROP
MOISTURE CONDITIONS USING PASSIVE MICROWAVE

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Introduction

Large scale crop condition monitoring is severely hampered by the lack of information on soil moisture conditions. Conventional soil moisture measurement techniques are simply too unwieldy and time-consuming to provide the density of data required. Even in the Great Plains, modeling of soil moisture from meteorological, geophysical, and crop information is not practical, due to the very limited input data available on a real-time basis. Yet, moisture information is vital in any effort to monitor crops such as winter wheat over large areas for conditions that impact cultural practices, growing conditions and, ultimately yield.

Passive microwave remote sensors have the capability to provide useful crop moisture information with sufficient time and space resolution. Several studies have demonstrated that brightness temperatures from sensors such as the Electrically Scanning Microwave Radiometer (ESMR) and the Scanning Multifrequency Microwave Radiometer (SMMR) are highly correlated with significant rainfall events over large agricultural areas. The resolution is of the order of 25 km spatially and every two or three days temporally, which is entirely adequate for large scale crop moisture monitoring. This proposed research is to develop an early warning screening program for moisture deficiencies or excesses at planting time and critical growth periods and an index of accumulated crop moisture and plant stress for the wheat areas of the Great Plains.

Passive Microwave Remote Sensing

Investigations by Cihlar and Ulaby (1975), Schmugge, et al. (1974, 1976a, 1976b, and 1977), Schmugge (1976 and 1977), and Newton (1977) demonstrated that the emitted radiation at microwave frequencies is a function of the moisture content of the emitting soil layer. Basically, air and dry soil have a very low dielectric constant, while that of water is the highest of naturally occurring abundant substances. As water is added to the soil, the dielectric constant of the soil, air, and water mixture increases, with a resulting decrease in the emissivity. The emissivity is related to the radiation received at the sensor antenna through the simplified relationship:

$$T_B = T_{EL} \quad (1)$$

where T_B is the radiation received, also termed the brightness temperature since it is linearly and directly proportional to the actual temperature of the emitting layer T_{EL} . The emissivity is ϵ . At wavelengths of 1.55 cm, the dry soil emissivity will normally be in the .92 to .95 range, while emissivities in areas receiving heavy rains will be as low as .74. At these relatively short wavelengths, the emitted radiation is absorbed and reflected by surface roughness and vegetative cover, which vary considerably from one area to the next. Attempts to quantitatively map soil moisture with 1.55 cm passive microwave remote sensors have not been particularly encouraging (for example, see Meneely, 1977). However, time series of brightness

temperature for the same sensor footprint areas (where surface roughness and vegetative cover variations are significantly reduced) show a high correlation with rainfall history and infrared soil moisture for essentially bare soils (see McFarland and Blanchard, 1977; Theis, 1979; Blanchard, 1981a; and Blanchard, 1981b).

In these studies in the Great Plains winter wheat areas, the brightness temperatures from the Electrically Scanning Microwave Radiometer (ESMR) on the Nimbus 5 spacecraft, and the rainfall and temperature records from the Climatological Data were objectively analyzed to a 25 km grid using a modified Barnes exponential weighting function. The grid established for the intensive study area of Oklahoma is shown in Figure 1. This grid is based on a polar stereographic map projection, true at 35°N, in order to accept latitude/longitude coordinates for input data. With this grid and the objectively analyzed values at each grid point, problems with missing data, variable spatial and temporal densities of input data, and data management are simplified.

Investigations with ESMR

Twenty-seven grid locations were selected for analysis of the ESMR data. The location of these grid cells in Kansas, Oklahoma, and Texas is shown in Figure 1. Each grid cell represents a 25 km square area in a county with a substantial acreage of winter wheat. The wheat acreage in each of the approximately equal area counties for the winter wheat in 1973-74 and 1974-75 is in Table 1.

The ESMR data set consisted of brightness temperature observations from September 5, 1973 to May 30, 1975. Approximately 260

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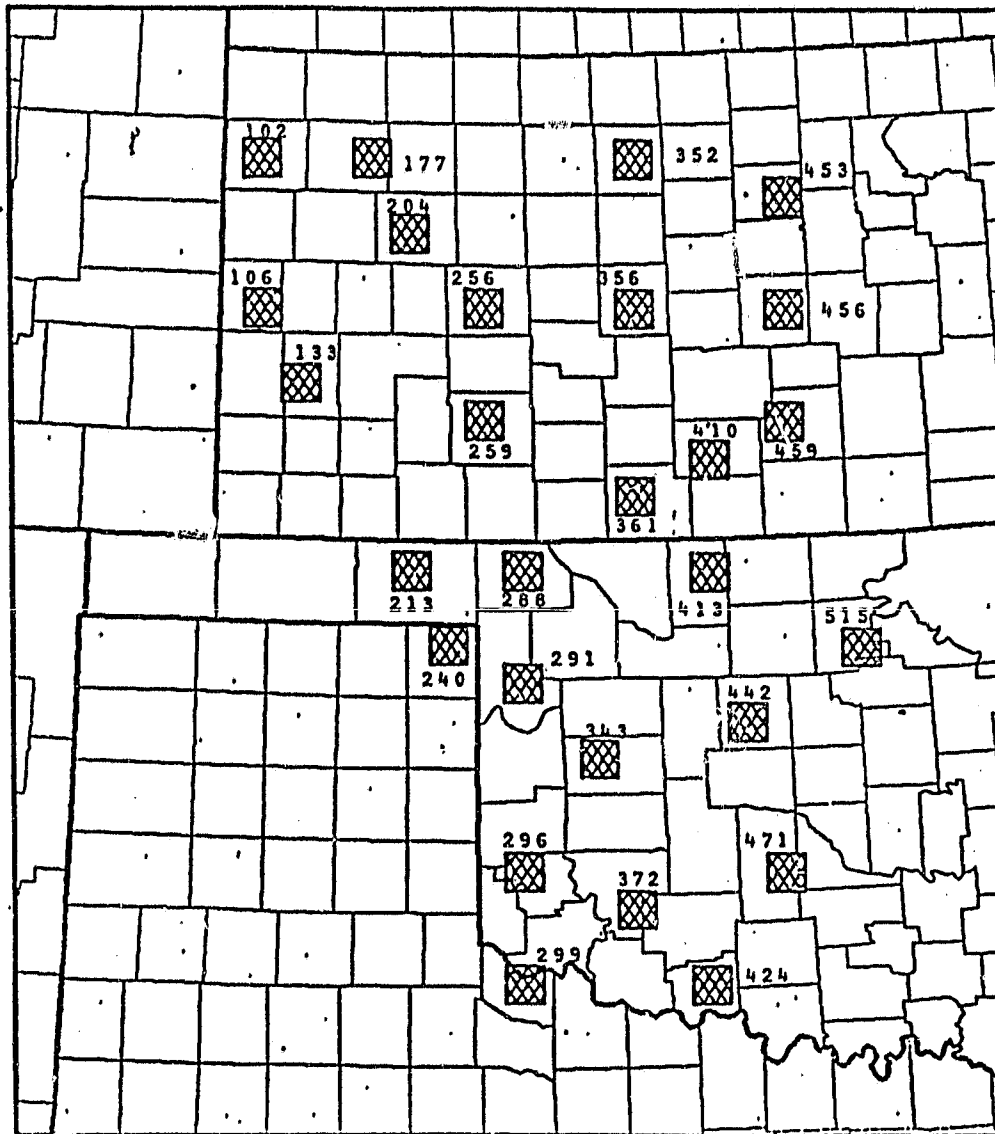


Figure 1. Location of Grid Cells for ESMR Analysis.

Table 1. Winter Wheat Acreage and Yield in the ESMR Grid Cell Counties.

<u>Kansas</u>						
<u>District</u>	<u>Grid</u>	<u>County</u>	<u>Planted Acreage</u> (1000s ha)		<u>Yield</u> (T/ha)	
			<u>1973-74</u>	<u>1974-75</u>	<u>1973-74</u>	<u>1974-75</u>
Northwest	102	Sherman	79	79	2.4	2.0
	177	Thomas	94	93	2.3	2.1
West Central	106	Greeley	78	83	2.3	1.6
	204	Gove	57	58	2.1	2.5
	256	Ness	75	80	1.8	2.0
Southwest	133	Kearney	58	60	2.2	1.6
	259	Ford	99	99	1.7	1.9
North Central	352	Osborne	58	60	1.4	1.9
	453	Ottawa	63	68	2.0	2.0
Central	356	Barton	95	99	1.3	1.9
	456	McPherson	94	103	1.9	2.0
South Central	361	Barber	69	72	1.7	1.8
	410	Kingman	96	101	1.8	1.9
	459	Sedgwick	106	113	1.8	1.8
<u>Texas</u>						
Northern High Plains	240	Lipscomb	49	60	0.6x7	1.2
Northern Low Plains	299	Hardeman	52	64	0.9x6	1.5
<u>Oklahoma</u>						
Northwest	213	Beaver	122	131	0.6	0.9
	288	Harper	68	71	1.4	1.2
	291	Ellis	48	51	0.9	1.0
West Central	343	Custer	100	113	1.7	1.9
Southwest	296	Greer	40	42	1.1	1.5
	372	Kiowa	107	118	1.3	1.7
	424	Cotton	64	66	1.7	1.4
North Central	413	Alfalfa	125	133	1.9	1.9
	515	Noble	60	58	1.7	1.9
Central	442	Kingfisher	115	126	1.4	1.7
	471	Grady	39	41	1.5	1.9

(to convert to bu/ac, divide by 0.0673).

observations of ESMR brightness temperatures were included in the analysis for each grid cell. The only significant break in the period of record occurred between June 8, 1974 and August 20, 1974 when only two days with ESMR coverage were noted in the central portion of the grid. For the period September 5, 1973 to May 30, 1975 ESMR brightness temperatures were available, on the average, every 2.4 days.

The analysis grid is the same 25 x 25 km grid used in earlier phases of this study. Daily maximum and minimum air temperatures, daily precipitation, and snow depth from the NOAA Climatological Data were objectively analyzed to each grid location. A modified Barnes exponential weighting function using the seven nearest observations was used for the objective analysis. The ESMR brightness temperatures from magnetic tape provided by the NASA Goddard Space Flight Center were also objectively analyzed to each grid with the same function. Only those observations within 35 degrees from nadir were used, which corresponded to a resolution ranging from 25 km at nadir to about 50 km at 35 degrees scanning angle. Data were used when the ESMR coverage occupied only a portion of this grid; not all grids have ESMR values for any given day.

The emissivity model used in the investigation is:

$$\epsilon = T_B/T_A$$

where ϵ is the normalized emissivity

T_B is the brightness temperature from ESMR

T_A is the daily maximum air temperature at the grid

The emissivity obtained is an approximation of the true emissivity layer; a necessary approximation in order to remove the

effects of daily and seasonal temperature changes. The resulting emissivities are, however, very near the expected values and the seasonal temperature trend is effectively removed from the brightness temperatures, as shown in Tables 2 through 4.

Emissivities at 1.55 cm for smooth surfaces are (Schmugge et al. 1977)

Water at 20°	0.40	0.40
Dry soil		0.94
Wet soil above field capacity		0.60
Pure ice		0.92

The emitting surfaces for ESMR observation however are rough, which increases the emissivity. Choudhury et al. (1979) reported the effect of roughness as:

$$= (1 - \epsilon_s)(1 - \exp^{-h})$$

where Δ is the change in emissivity from the smooth surface emissivity, ϵ_s , for a roughness h . Their data showed the best correlations for observed emissivities over rough fields at the Phoenix site (aircraft observations) were from a roughness of 0.6. If this figure is used, the emissivity for a moist, rough terrain is 0.74, which coincides well with the lowest emissivities observed in the ESMR data sets.

Correlations of Emissivity with Antecedent Precipitation

To correlate the normalized emissivity with the rainfall history of each test grid cell, an antecedent precipitation index (API) was used (McFarland, 1975; McFarland and Blanchard, 1977; Blanchard, et al. 1981). The API model used is:

$$API_i = API_{i-1} k(t) + (r_i)^{0.891} \quad (1)$$

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Table 2. Fall Correlations of API and Emissivity.

GRID	Mean Emissivity	Mean API	Grid Cell R-Squared	Averaged Grid Cell R-Squared
102	.92	.40	.29	.30
106	.91	.43	.46	.47
133	.92	.29	.17	.21
177	.92	.39	.30	.31
204	.92	.45	.43	.42
213	.91	.61	.27	.29
240	.92	.78	.28	.28
256	.90	.47	.54	.50
259	.90	.64	.49	.51
288	.90	1.34	.45	.46
291	.92	.70	.32	.34
296	.89	.95	.49	.53
299	.89	.95	.49	.54
343	.89	.87	.57	.56
352	.90	.85	.37	.40
356	.87	1.03	.47	.48
361	.90	1.12	.54	.56
372	.90	.93	.31	.35
410	.88	1.17	.44	.44
413	.88	1.12	.57	.60
424	.90	.98	.52	.40
442	.89	1.07	.38	.41
453	.89	1.16	.31	.34
456	.88	1.20	.44	.43
459	.88	1.17	.41	.44
471	.90	.93	.19	.18
515	.90	1.20	.17	.21

Table 3. Summer Correlations of API and Emissivity.

GRID	Mean Emissivity	Mean API	R ²
102	.94	.65	.37
106	.92	.47.	.55
133	.92	.79	.59
177	.93	.52	.45
204	.93	.77	.54
213	.92	.56	.36
240	.92	.58	.29
256	.92	.59	.42
259	.92	1.13	.28
288	.91	.94	.48
291	.91	.85	.16
296	.90	1.13	.39
299	.90	1.10	.42
343	.90	1.12	.40
352	.92	.71	.34
356	.90	.79	.53
361	.92	.96	.63
372	.91	1.23	.40
410	.91	.81	.57
413	.90	1.24	.32
424	.91	1.61	.48
442	.90	1.47	.41
453	.91	.96	.33
456	.91	.92	.51
459	.91	1.08	.31
471	.90	1.43	.47
515	.90	1.04	.25

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Table 4. Spring and Winter Correlations of API and Emissivity.

GRID	Spring			Winter		
	Mean Emissivity	Mean API	R ²	Mean Emissivity	Mean API	R ²
102	.91	.52	.22	.91	.40	.04
106	.91	.21	.10	.91	.11	.05
133	.91	.48	.06	.91	.28	.01
177	.91	.59	.12	.91	.30	.03
204	.91	.68	.24	.91	.51	.11
213	.91	.51	.15	.91	.29	.04
240	.91	1.08	.37	.91	.37	.04
256	.91	.88	.08	.91	.55	.26
259	.91	1.15	.06	.90	.50	.15
288	.90	1.08	.18	.90	.73	.05
291	.91	.89	.22	.91	.46	.09
296	.89	1.29	.35	.89	.44	.42
299	.90	1.10	.11	.90	.38	.19
343	.89	1.34	.23	.90	.57	.20
352	.90	.95	.09	.90	.63	.16
356	.88	1.04	.13	.88	.76	.25
361	.90	1.28	.13	.90	.59	.09
372	.90	1.27	.18	.90	.54	.30
410	.89	3.24	.21	.89	.64	.17
413	.87	2.09	.39	.90	.73	.28
424	.89	1.59	.28	.89	.70	.14
442	.87	2.23	.43	.88	1.15	.31
453	.89	1.20	.12	.90	.89	.09
456	.88	1.81	.24	.89	.93	.12
459	.88	2.02	.14	.88	1.03	.23
471	.88	1.98	.35	.89	.74	.11
515	.88	3.33	.38	.88	1.71	.16

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The recession coefficient, k , as a function of time was developed from a cosine wave to simulate the annual change in evapotranspiration. The lowest value of the recession factor was 0.70 in August; the highest value was 0.92 in January.

The exponential 0.891 was used to convert rainfall to effective rainfall, which is that portion of rainfall entering the soil for crop use. The exponential was applied to the rainfall expressed in mm, then the cm equivalent was added to the previous day's index.

The API model was used for all grid cells without regard to soil texture or hydrologic response differences. Soil texture has a pronounced effect on microwave response to soil moisture changes (Schmugge, 1980; Wang and Schmugge, 1980). With the same moisture content by weight, a sandy soil will have a lower emissivity than a clay soil due to the greater amount of water in larger pore sizes. Schmugge (1980) reported brightness temperature differences of 20 K in measurements at 1.55 cm from aircraft sensors over fields in the Phoenix AZ area. He reported that conversion of the soil moisture parameter to percent of field capacity would normalize each soil texture for microwave response to soil moisture. Thus, a geophysical data base that includes soil texture would greatly facilitate spatial mapping of soil moisture for crop condition assessment from fallow to stand establishment.

Similarly, the recession factor could be modified to take the hydrologic response (e.g., surface runoff and drainage) and the evaporation climatology into account for each grid cell.

To correlate the emissivity with API, four seasons were defined, shown in Table 5. The fall (Season 3) correlations are shown in Table 2.

Table 5. Seasons for Emissivity Correlations.

Season	Wheat Development	Period
1 Spring	major growth	Feb 1 to Apr 30
2 Summer	harvest; fallow	May 1 to Jul 31
3 Fall	planting; stand establishment	Aug 1 to Oct 31
4 Winter	dormancy	Nov 1 to Jan 31

The number of observations ranged between 64 and 71 for the two years (1973 and 1974) of data in the correlations. The coefficients of determination (R) for the test grids range from 0.17 to 0.57, which strongly supports a relationship between emissivity and API. The significance level is .02 percent for 0.17 and .01 percent for 0.57.

To determine a sensitivity of the correlations to the size of the grid cell, the averaged emissivity for five grids centered upon the test grid was correlated with the averaged API. This approximated correlations for a 50 km square grid cell, which is the resolution of some SMMR and SMMI radiometers. The coefficients of determination (R) presented also in Table 2 do not show any significant differences from the R for the grid cell. A very slight improvement was noted from most grids.

The differences in coefficients of determination from one grid cell to the next are due to several factors, including the inadequacies of the API model to describe the moisture content of the emitting layer. Differences in vegetation that masks the emitting layer and hydrological response of each location are primary contributors to

the varying correlations. A recession factor for each grid cell could be developed to take these factors into account, at least empirically. A major conclusion from this aspect of the study is that, while spatial mapping of emissivity data will provide qualitative information on crop moisture, temporal mapping will provide quantitative data on crop moisture. Temporal mapping will require the refinement of crop moisture models for each general area to take vegetation and hydrological response differences into account.

The summer season coefficients of determination, presented in Table 3, show a slightly higher (16 of the 27) level of correlation. The number of observations ranged from 38 to 43.

The winter and spring coefficients are predictably much lower as a result of increased vegetation for all sites and the influence of snow and frozen ground. These are shown in Table 4. The number of observations in the spring ranged from 69 to 75. The range for winter was 82 to 89.

Snow, ice, and frozen soils have an emissivity similar to that of dry soil since the dielectric constant of ice is near that of dry soil. In the analysis, the rainfall equivalent of the reported snowfall was accumulated then released on the first day that no snowcover was reported. The data in Table 4 included all days with a reported emissivity. The coefficients of determination improved when the analysis was reaccomplished with all days with snow cover excluded. For the spring season, the R average increase was 0.10 for all 27 test grid cells. Most of the increase was due to a few grid cells, which are shown in Table 6.

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Table 6. Correlations of API and Emissivity for Spring
with Snow Days Excluded.

GRID	R^2 - All days	R^2 - No snow	No. snow days
213	.15	.31	21
240	.37	.58	22
356	.13	.27	28
413	.39	.57	27
453	.12	.40	28
456	.24	.59	30
459	.14	.33	31
471	.35	.50	28
515	.17	.38	21

For the winter season, the coefficients of determination for several grids showed comparable increases, but some decreases were also noted. There was an indication from the air temperature records that the snow reports did not represent a uniform snow cover, however.

A fairly typical emissivity behavior through a period with snow and frozen ground is shown in Table 7. Note the rapid and sustained increase in brightness temperatures to 0.95 and 0.96 when the temperatures of the emitting layer were apparently below freezing. The emissivities remained high without any response to the precipitation that was reported on days 365 through 368. The emissivity dropped to 0.86 after the maximum air temperature climbed well above the freezing point.

Scatterplots for selected grid cells for each season are contained in Appendix A. The winter and spring season correlations were performed without snow days.

In a clear, dry atmosphere, the scattering and absorption of microwave radiation is negligible. With increasing water vapor, the transmissivity decreases, but remains above 90 percent. At 1.55 cm wavelengths, a vapor total of two centimeters will attenuate only about five percent of the emission (Gloersar and Barath, 1977). Thus, for practical purposes, a cloud-free atmosphere is transparent at 1.55 cm.

Ice clouds and clouds composed of small water droplets similarly are transparent for practical purposes. Larger water droplets in clouds and precipitation size droplets (millimeter size) are strong reflectors and absorbers of microwave emission, especially in the shorter wavelengths. A more-or-less typical thunderstorm with a

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Table 7. Effect of Low Temperatures on Emissivity
for a Grid in Harper County, Oklahoma.

Julian Day, 1973	Rainfall or Rain Equiv. (cm)	Brightness Temperature (°C)	Maximum Air Temperature (°C)	Normalized Emissivity
337	0.20	-	-	-
338	2.45	-	-	-
347	-	256	13.1	.89
352	-	254	9.3	.90
358	0.01	-	-	-
359	0.04	253	6.6	.91
363	0.11	256	10.3	.90
364	-	264	1.9	.96
365	0.38	-	-	-
366	0.57	250	-9.6	.95
367	1.12	-	-	-
368	0.01	254	-6.8	.96
370	-	253	-8.2	.96
371	-	255	-6.8	.96
372	-	256	-2.2	.95
373	-	252	1.7	.92
376	0.05	-	-	-
382	0.01	249	16.5	.86
383	0.37	-	-	-
384	-	256	10.5	.90

vertical extent of 10 km and a rainfall rate of 5 mm/hr will attenuate 94 percent of 1.55 cm radiation passing through the cloud. Thus, rain clouds in particular will mask the radiation emitted at the surface. The liquid water of the clouds and thunderstorm is, however, emitting microwave radiation also as a function of temperature and emissivity. Paris (1969) reported downwelling radiation at 23 GHz from a heavy rain to be 255 K and from a light rain of 200 K, the emissivities of rain clouds are of the order of 0.71 to 0.90. These emissivities are in the same range as the emissivities of moist soils.

Thus, thunderstorms in the field of view of ESMR or SMMR will not produce a noticeable departure in brightness temperatures unless the surrounding area is very dry and hot. The emissivities from a moist soil and from a thunderstorm would be very similar.

In terms of ESMR as an all-weather sensor, the distinction between surface emission and atmospheric emission may not be necessary. The API model based on 24-hour precipitation totals will not describe thunderstorms in the field of view, but in general the surface and atmospheric emissions are in the same sense for both a dry surface - clear atmosphere and a wet soil - raining atmosphere.

An examination of several days with extensive, heavy thunderstorms at the time of the Nimbus-5 overpass confirms the expected effects on the surface microwave emission. On September 26 and October 12, 1973, the 1735Z radar facsimile chart of the National Weather Service showed over five-tenths coverage of moderate or greater intensity thunderstorms over south central Kansas and north central Oklahoma. The October 12 storms produced especially heavy rains, with a 50 cm plus rainfall center near Enid, Oklahoma. The

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lowest brightness temperature observed for the flood was 215 k which corresponds to an emissivity of 0.75 for an emitting temperature of 287 k. The normalized emissivities for the seven test grid cells in the storm area averaged 0.83 on September 26 and 0.82 on October 12. Lowest emissivities were 0.76 on October 12 and 0.81 on September 26.

Crop Condition Assessment

The seasonal crop development calendars and the weekly crop weather reports for Oklahoma showed normal fall planting and stand establishment for the fall of 1974, but extensive delays beginning in October 1973. Table 8 contains a summary by week for planting for the winter wheat in Oklahoma.

The delays in seeding, especially in the West Central, North Central, and Central crop reporting districts, were also commented upon in the weekly crop-weather reports (USDA-USDC Weekly Weather and Crop Bulletins). In addition, to the state percentages, the report for the week ending October 8, 1973 stated that seeding was 1 to 2 weeks behind normal. In contrast, the planting activity in the fall of 1974 was more-or-less normal. Above normal rains in August provided adequate soil moisture for seeding; subsequent rains did not cause widespread delays.

The time series plot of emissivity and API for grid cells 413 and 343 show the rainfall events that produced the delays. These plots are shown in Figures 2 and 3.

The wet fall that hampered wheat seeding was more pronounced in Kansas in 1973. The state average precipitation was 21.21 cm (8.35 in) compared with 6.71 cm (2.64 in) normal for September. October was also wet with 8.15 cm (3.21 in) compared with a normal of 4.75 cm

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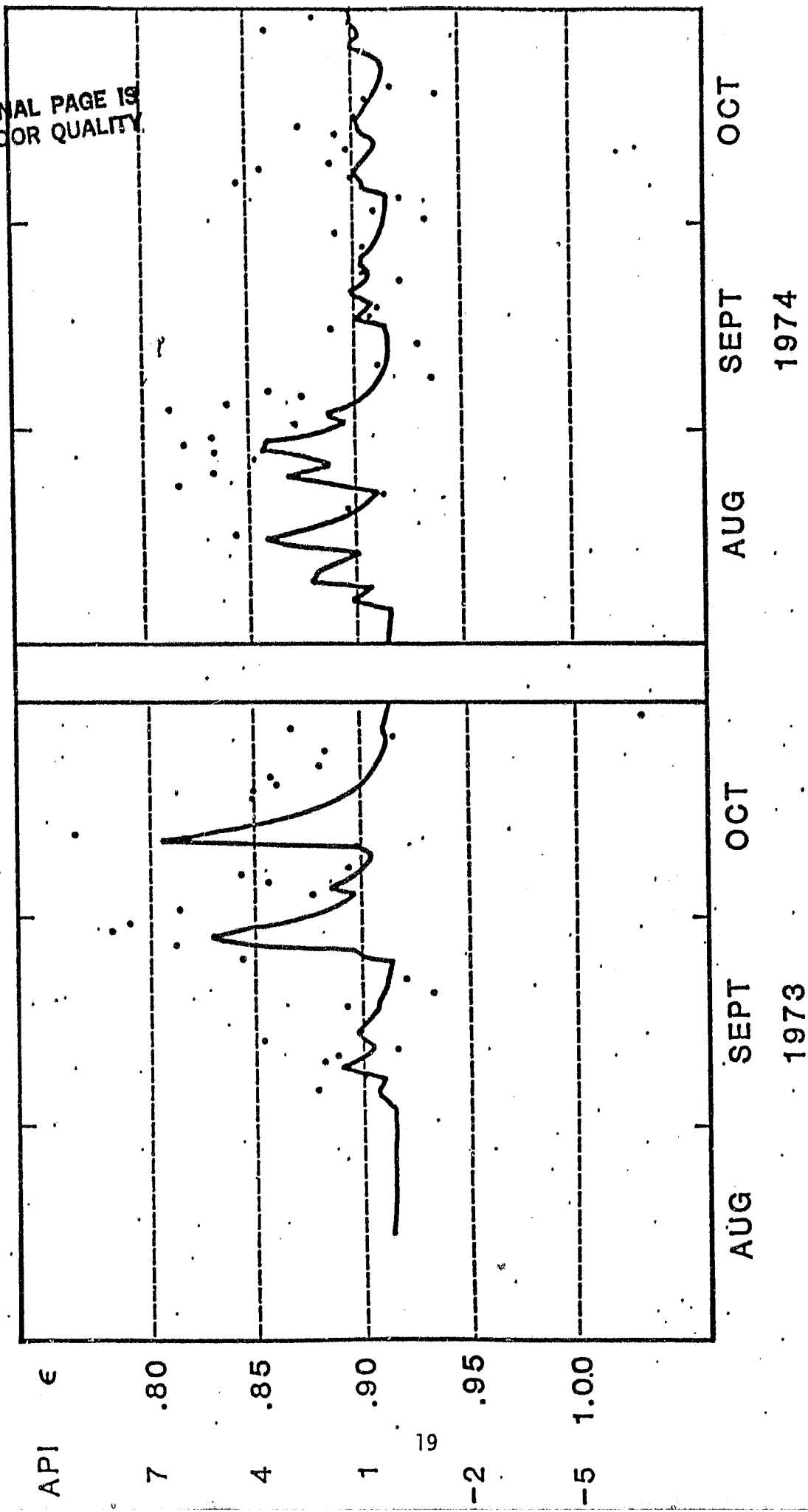


Figure 2. Time Series Plot of Grid 413 Emmissivity and API for Season 3.

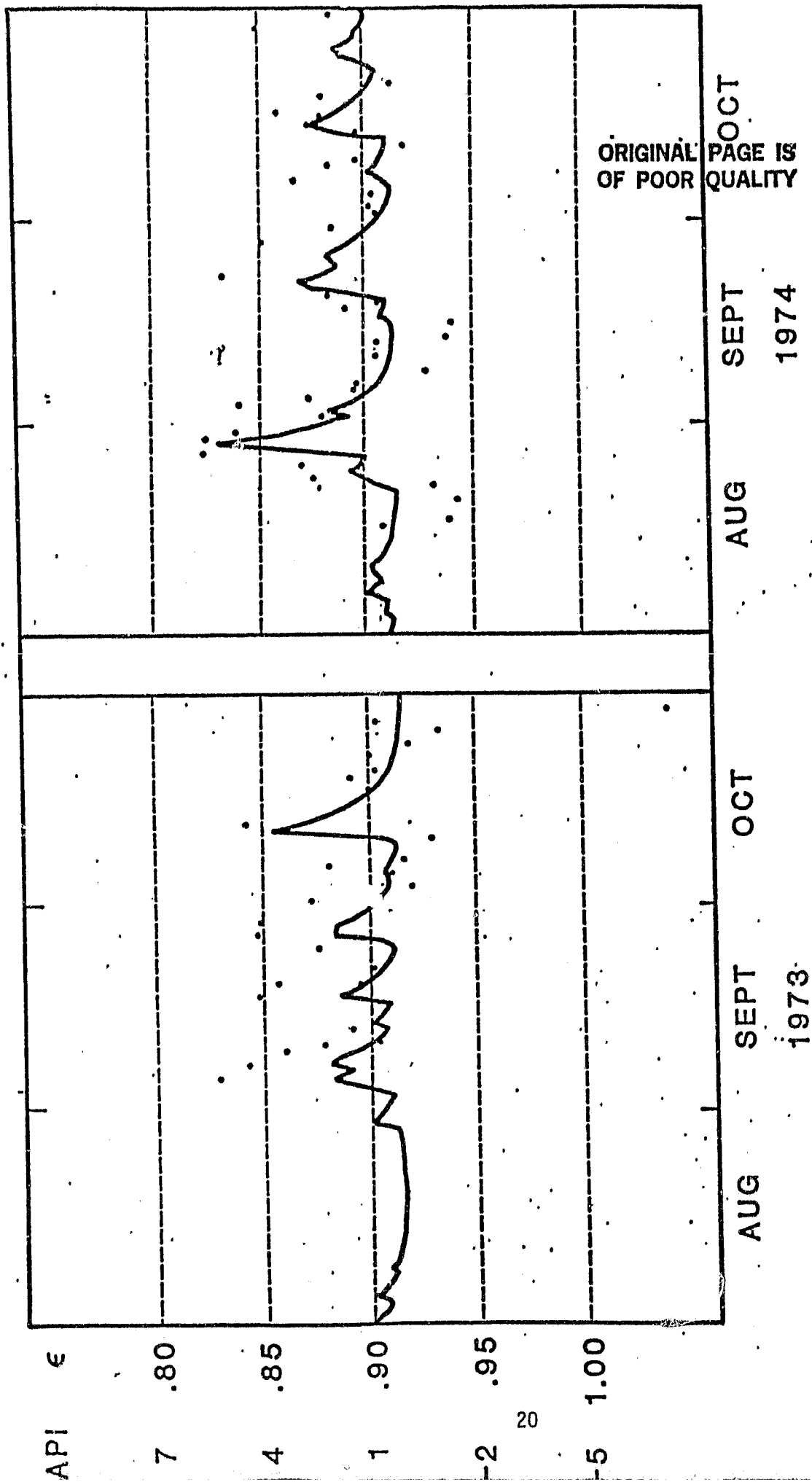


Figure 3. Time Series Plot of Grid 343 Emissivity and API for Season 3.

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Table 8. Seeding Progress in Oklahoma for the Fall of 1973 and 1974.

Crop Reporting District (and grid cells)		Sep 14- Sep 15	Sep 21- Sep 22	Sep 28- Sep 29	Oct 5- Oct 6	Oct 12- Oct 13	Oct 19- Oct 20
State Average	1973	14	25	41	53	75	80
	1974	11	31	38	65	88	95
Northwest (213,288,291)	1973	55	71	--	88	--	98
	1974	41	--	93	99	--	100
West Central (343)	1973	5	13	--	52	--	84
	1974	8	--	30	67	--	98
Southwest (296,372,424)	1973	6	11	--	47	--	74
	1974	5	--	15	30	--	86
North Central (413, 515)	1973	5	15	--	35	--	69
	1974	1	--	28	65	--	96
Central (442, 471)	1973	7	24	--	53	--	85
	1974	6	--	37	63	--	93

(1.87 in). Extracts from the weekly crop weather reports stated:

September 17 Rains delay planting and seedbed preparation. Planting is 10% complete compared with 15% a year ago.

September 24 Rains delay planting and seedbed preparation. Planting is 20% complete compared with 35% a year ago.

October 1 Considerable reseeding is expected due to heavy rain.

October 8 Seeding is 10 days behind normal, Seeding is 35% complete compared with 85% last year.

October 15 Seeding is 55% completed compared with 95% last year.

October 22 Seeding is two weeks behind at 65% complete, compared with 100% last year.

In contrast, 1974 had normal progress statewide through the fall. August had 11.10 cm (4.37 in) compared with a normal figure of 7.65 cm (3.01 in). This guaranteed good planting moisture. September was on the dry side, with 4.17 cm (1.64 in) compared with a normal of 6.71 cm (2.64 in).

Time series plots for two grid cells in Kansas are shown in Figures 4 and 5. In each of the figures, the low emissivities that are indicative of the heavy or frequent rains are evident in 1973. The contrast with the same period in 1974 is also evident. A separate portion of this research addresses the discrimination capabilities of the use of emissivity data to discern precipitation events that can be related to progress in field work and stand establishment.

Microwave Remote Sensing of Crop Stress

The emitted microwave radiation from the soil is scattered and attenuated by vegetation. This is a function of wavelength; the scattering and attenuation are much more pronounced at the shorter wavelengths such as the 1.55 cm of ESMR and SSMI and the 1.36 and 1.66 cm wavelengths of SMMR. As the vegetative cover of the crops increases,

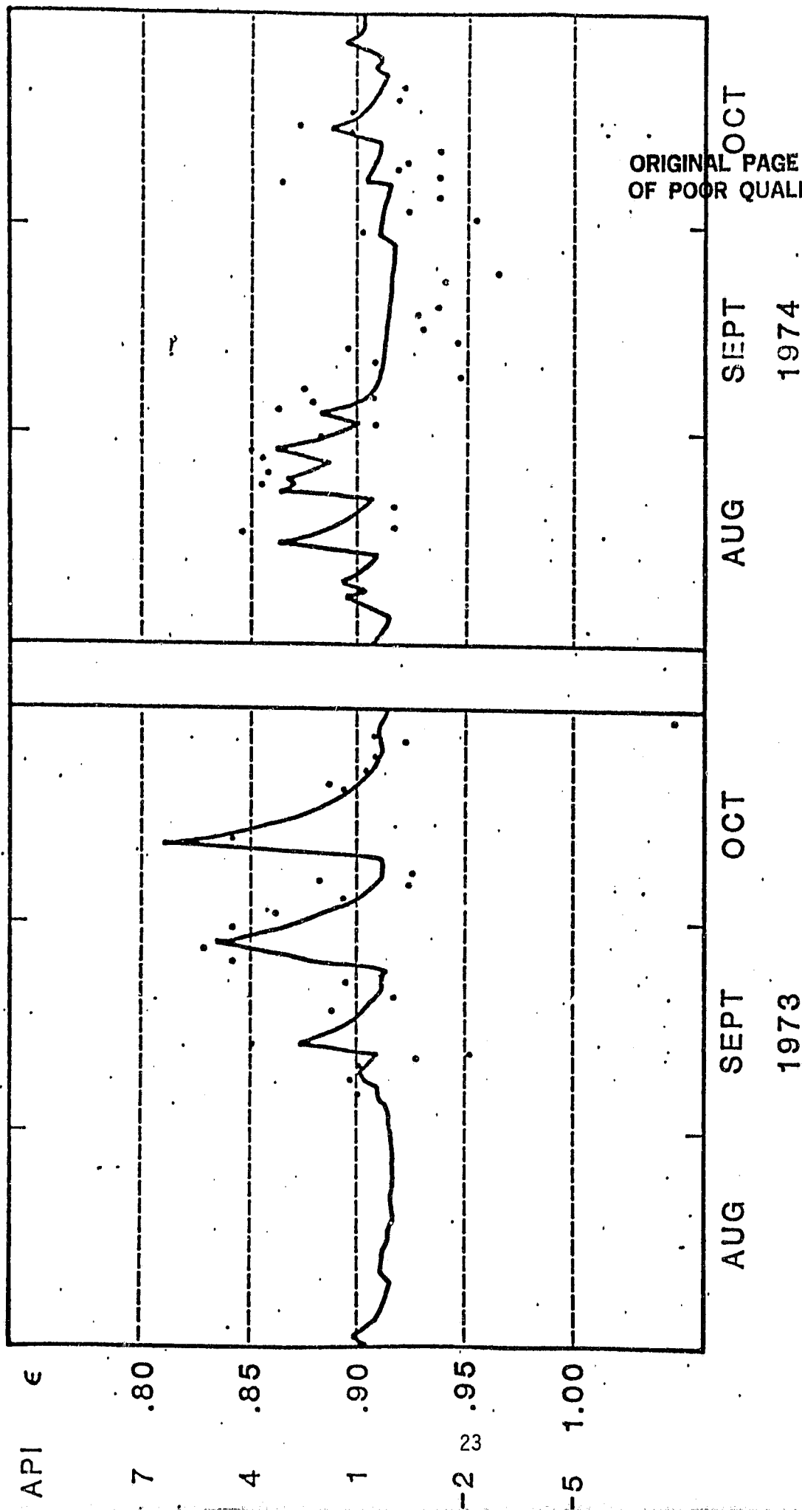


Figure 4. Time Series Plot of Grid 461 Emissivity and API for Season 3.

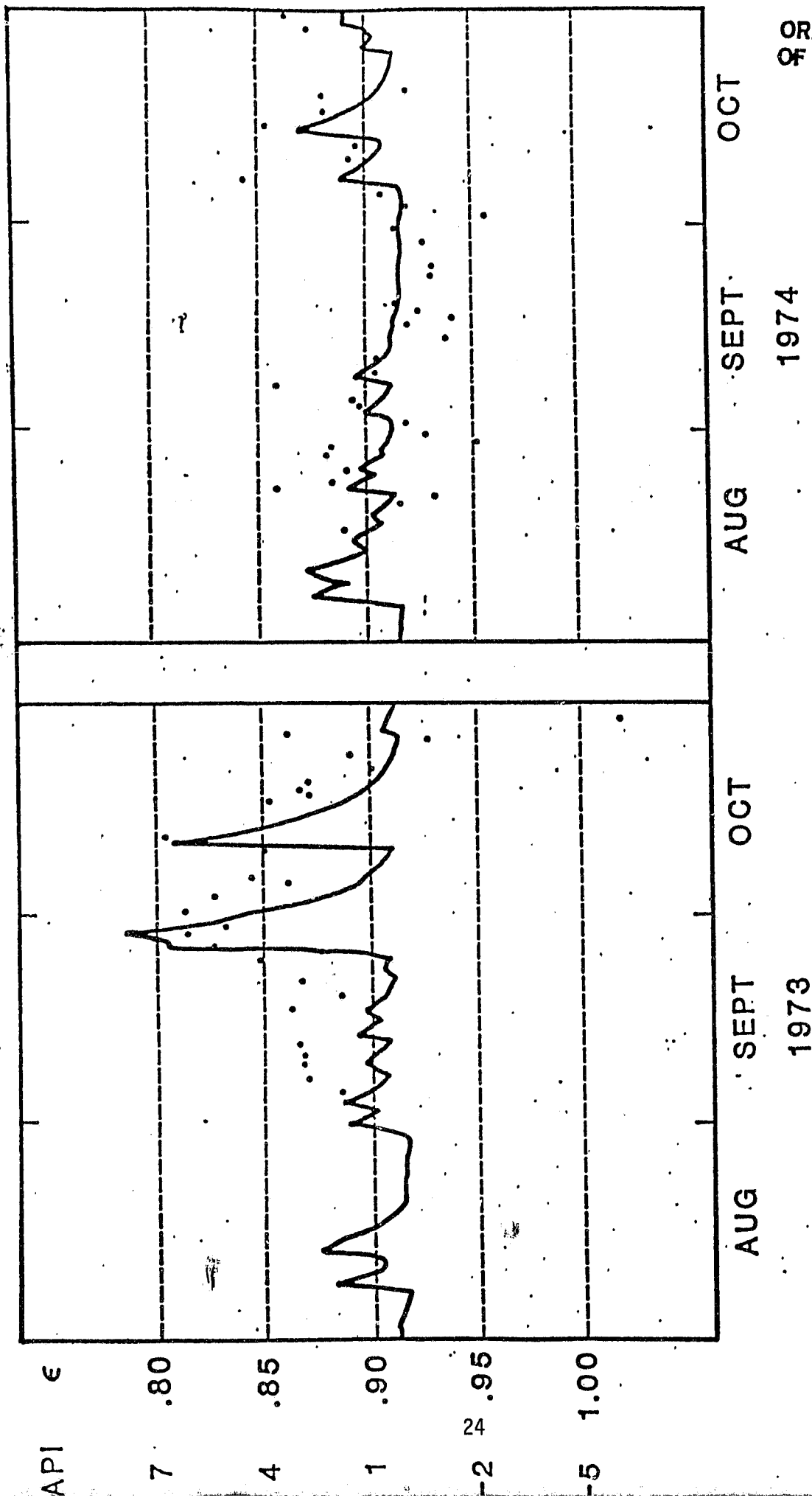


Figure 5. Time Series Plot of Grid 456 Emissivity and API for Season 3.

the soil component of emission received at a sensor above the canopy will decrease. However, the canopy is also emitting radiation as a function of its emissivity and temperature. Mo, et al. (1981) found the effective canopy thickness to be directly proportional to the amount of water present in the plant materials.

For a crop with adequate moisture, the canopy temperature will be at or below the air temperature in mid-day due to the cooling effects of evapotranspiration. Further, the high moisture content of the crop will decrease the emissivity. Thus, the brightness temperature of a well-watered crop will be lower than that of a crop experiencing moisture stress. In addition, plants under moisture stress often exhibit leaf rolling or wilting, which decreases the attenuation and scattering. More of the soil surface is also exposed, so the net effect is for a greater component of emission from the dry soil to reach the sensor. The net effect is for the brightness temperatures to respond in the same sense for a well-watered crop and an moist soil surface. Low brightness temperatures and low emissivities are indicative of adequate crop moisture, while high brightness temperatures and high emissivities are indicative of either a dry soil surface that, if persistent, could indicate insufficient crop moisture for plant and stand establishment or a crop canopy that is experiencing moisture stress.

The emissivities for grid cells with large winter wheat acreages conformed fairly well with expectations. For the months of April and May, the winter wheat canopies will be at their maximum extent. For a vigorous crop without moisture stress, the emissivity should be fairly constant with a very strong correlation with soil moisture, as

inferred by API. Table 9 shows the comparison of two grids in the winter wheat areas of Oklahoma for 1974 and 1975. Two periods were selected with varying rainfall and presumably soil moisture during periods when the winter wheat canopy should be fully developed.

For grid 413 with apparently adequate soil moisture, the emissivities were fairly constant in 1974 and 1975. The emissivities for corresponding periods for grid 213, with much less rainfall, were higher. Indications of moisture stress at these times are shown by the yields.

The correlation coefficients between API and emissivity for these grid cells for the periods show a range from -0.12 to -0.64, which is not surprising in view of the number of factors involved. The response of emissivity to rainfall, as indicated by the greater negative correlation coefficients, will be from several sources. Soil with little or no vegetative cover, emission and scattering in the atmosphere, and limitations of the simple models used will all contribute.

The major conclusions of this aspect of the investigation are:

1. A well-watered crop will have a decreased emitting temperature due to ET and a reduced emissivity due to an increased water content of the canopy. Both contribute in the same direction toward a decreased brightness temperature when compared to a crop under stress. The ESMR data support this concept.

2. The model developed by Blanchard, et al. (1981) has the potential for use as an early warning for moisture stress. The summation of daily departures of emissivity from the well-watered

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canopy emissivity (of 0.90) will be directly proportional to accumulated moisture stress of the crop. This should serve as an early warning screening device for yield reduction.

3. The simple models used have significant utility for an all-weather crop condition screening device for large relatively monoculture agricultural areas.

Table. 9 ESMR Microwave Emissivities from
Vegetated Terrain.

Grid	County(OK)	Planted Acreage (1000s ha)		Yield (T/ha)	
		1973-74	1974-75	1973-74	1974-75
213	Beaver	122	131	0.6	0.9
413	Alfalfa	125	133	1.9	1.9

	April 11 - May 6, 1974	May 4 - May 30, 1975
	Grid 213	
Number of Emissivity Obs.	15	15
Emissivity mean	.934	.916
Standard deviation	.020	.026
Total rainfall (cm)	0.10	9.45
API - emissivity correlation	-0.12	-0.64
	Grid 413	
Number of Emissivity Obs.	15	16
Emissivity mean	.896	.897
Standard deviation	.011	.019
Total rainfall (cm)	12.81	22.02 (Apr. 27-May 30)
API - emissivity correlation	-0.29	-0.51

RELATIVE FREQUENCY DISTRIBUTIONS

To provide a statistical approach to the identification of dry periods, a number of cumulative relative frequency distributions were computed. Four are shown in Figures 6 through 9. These frequency distributions relate emissivity to the precipitation history in a probabilistic manner.

The distributions were constructed for grid cell data using all 27 case study grid cells for season 3 (Aug, Sep, Oct). The following variables were defined.

<u>Variable</u>	<u>Definition</u>
RAIN0	Precipitation on Day of Observation
RAIN5	Rain0 + Amount for Previous 5 days
RAIN10	Rain0 + Amount for Previous 10 days
RAIN15	Rain0 + Amount for Previous 15 days
RAIN20	Rain0 + Amount for Previous 20 days

Additionally, five emissivity variables were defined.

<u>Variable</u>	<u>Definition</u>
ECAT0	Emissivity category for day of observation
ECAT5	Lowest emissivity category for day of observation and previous 5 days
ECAT10	Lowest emissivity category for day of observation and previous 10 days
ECAT15	Lowest emissivity category for day of observation and previous 15 days
ECAT20	Lowest emissivity category for day of observation and previous 20 days.

These emissivity categories were defined, to be determined from the minimum emissivity for the period defined:

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<u>Emissivity Category</u>	<u>Definition</u>
1	$\min(\text{EMIS}) < 0.78$
2	$0.78 < \min(\text{EMIS}) \leq 0.81$
3	$0.81 < \min(\text{EMIS}) \leq 0.84$
4	$0.84 < \min(\text{EMIS}) \leq 0.87$
5	$0.87 < \min(\text{EMIS}) \leq 0.90$
6	$0.90 < \min(\text{EMIS}) \leq 0.93$
7	$0.93 < \min(\text{EMIS}) \leq 0.96$
8	$0.96 < \min(\text{EMIS})$

Each of Figures 6 through 9 have several cumulative distribution curves, one for each of several values of ECAT. The interpretation of these curves is straightforward. For instance, Figure 6, the distribution of RAIN5 by ECAT5, shows that 90% of the days with ECAT5=5 ($0.87 < \min(\text{EMIS}) \leq 0.90$) had six-day rainfall of 1.3 cm or less. If these relative frequency distributions can be assumed to approximate true probabilities, a 6-day minimum emissivity higher than 0.90 (ECAT0 = 6) would indicate a probability of 99% that the rain for the day of observation and previous five days was no more than 1 cm.

The spacing of curves on these graphs indicates that emissivity data can be used to discriminate between relatively moist and dry crop soil moisture conditions; if this were not the case, all of the curves on any of the figures would approximately coincide with all of the others. In fact, the curves are nearly parallel and have approximately regular spacing over most of the emissivity range. It is only for the extremes of emissivity, where the sample sizes are small, that these relationships are not valid. Apparently, the true probability curves approximated by these sample distributions are well-behaved smooth curves arranged in order by the value of ECAT.

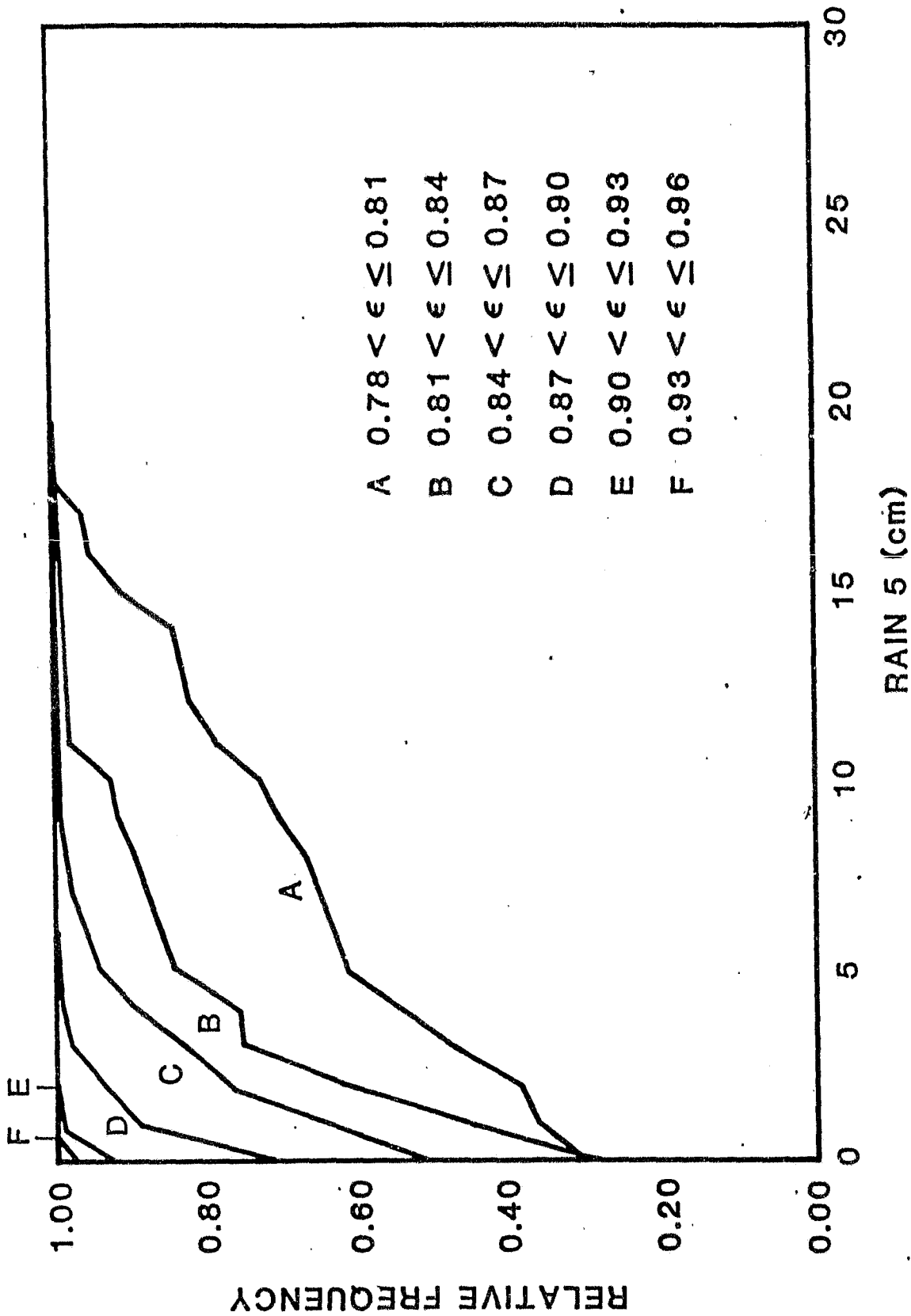


Figure 6. Cumulative Frequency Distribution of RAIN5 by ECAT5 for Season 3 (Aug, Sept, (Oct)).

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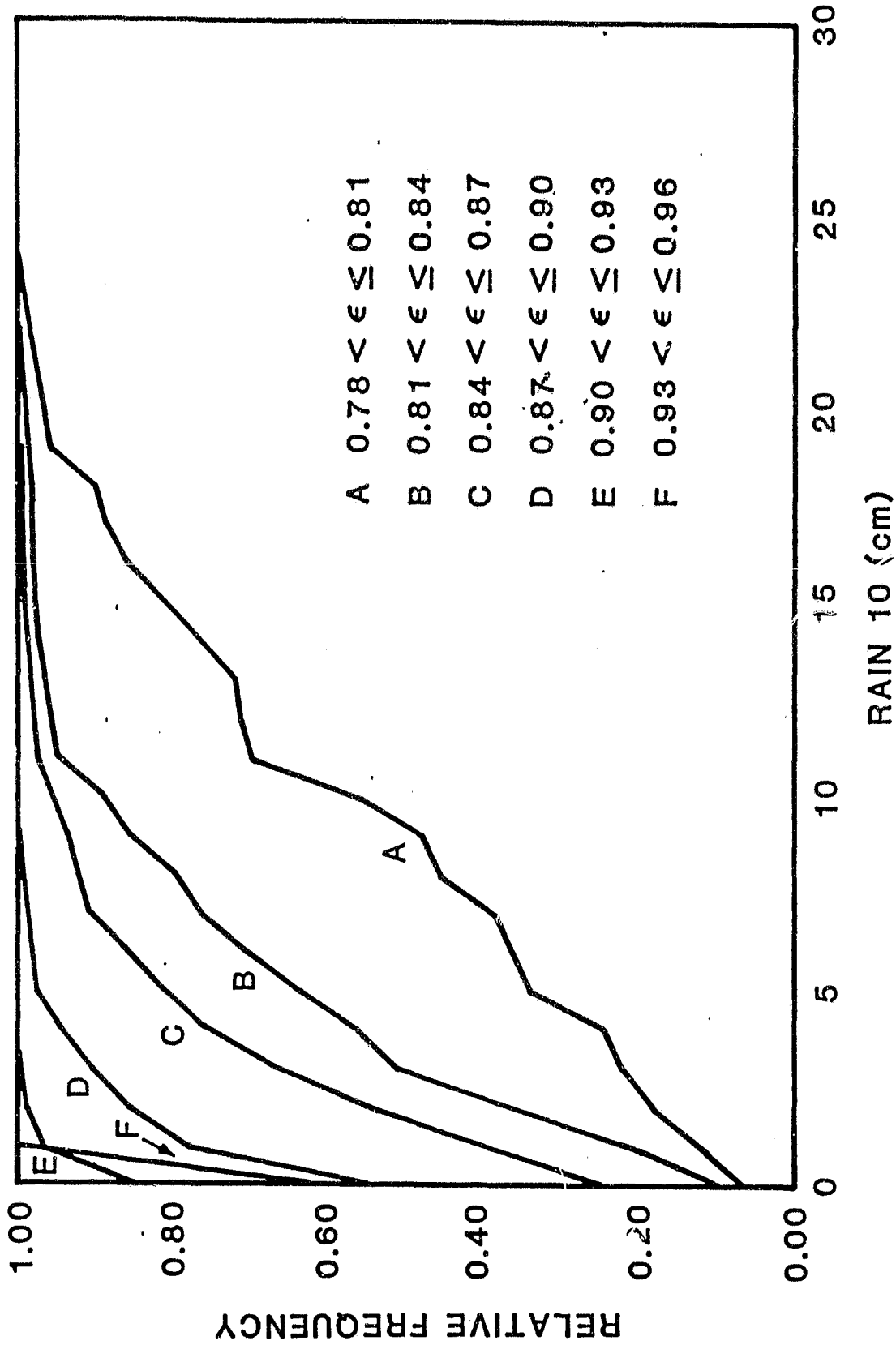


Figure 7. Cumulative Frequency Distribution of RAIN10 by ECAT10 for Season 3 (Aug, Sept, (Oct)).

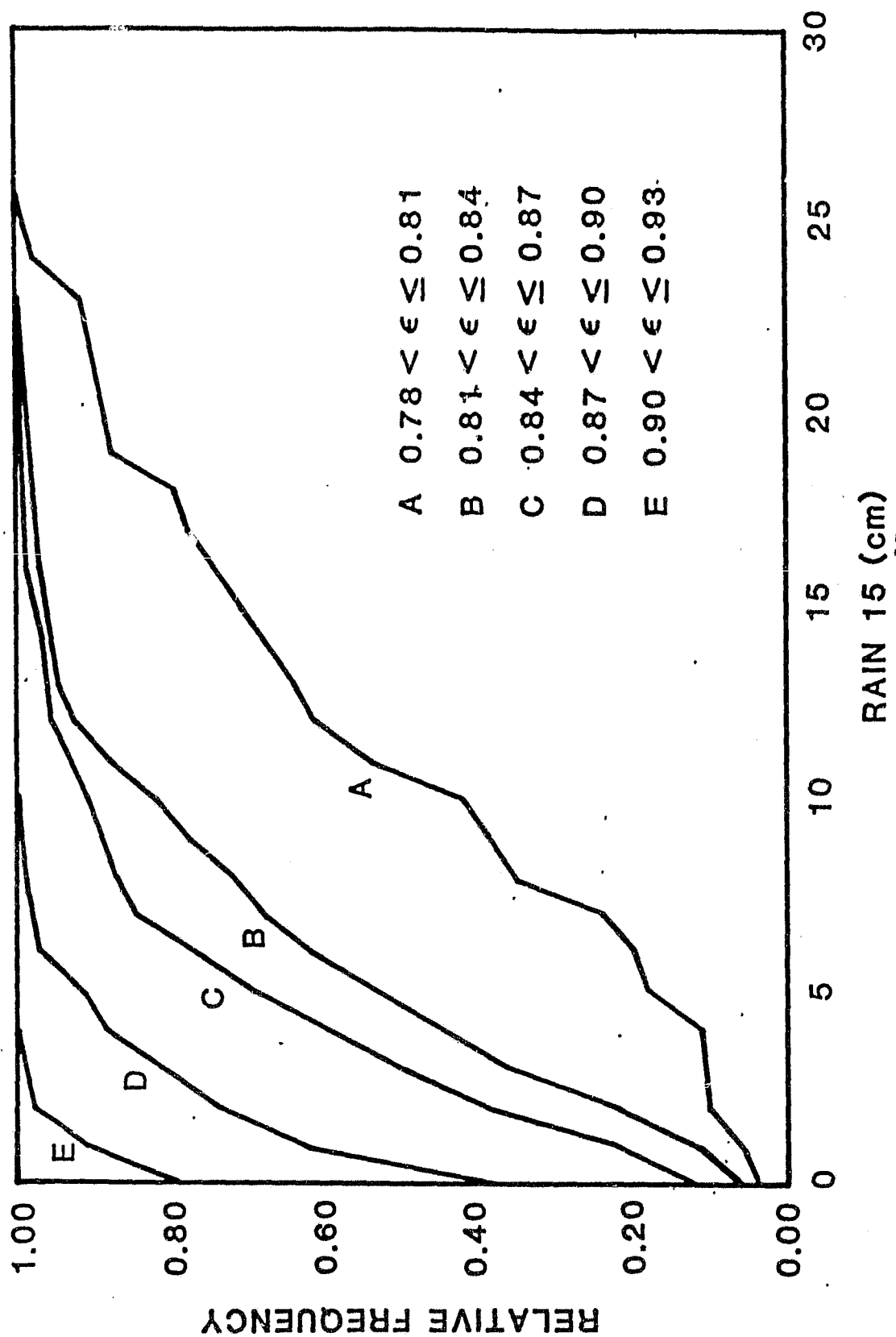


Figure 8. Cumulative Frequency Distribution of RAIN15 by ECAT15 for Season 3 (Aug, Sept, (Oct)).

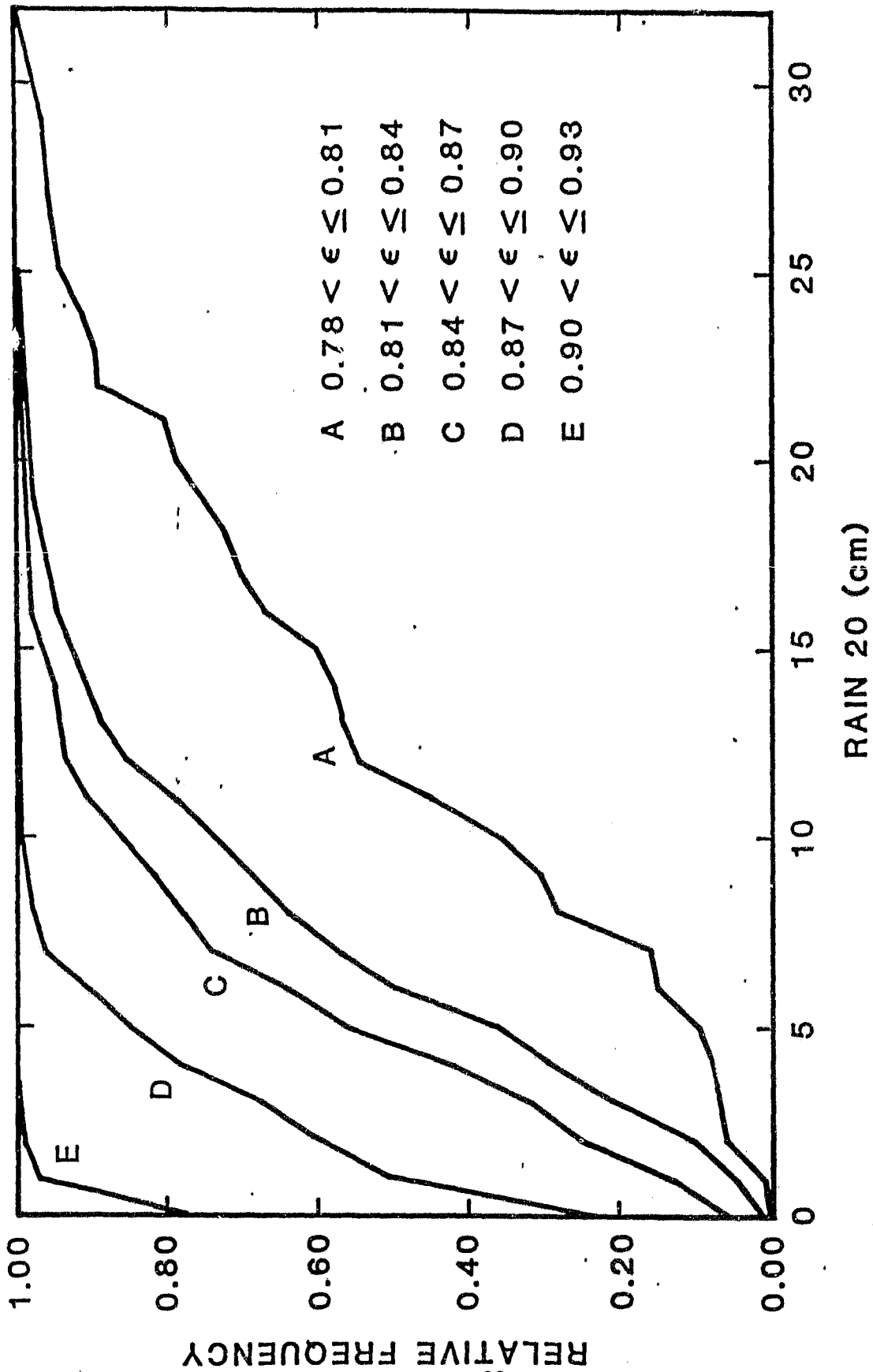


Figure 9. Cumulative Frequency Distribution of RAIN20 by ECAT20 for Season 3 (Aug, Sept, (Oct)).

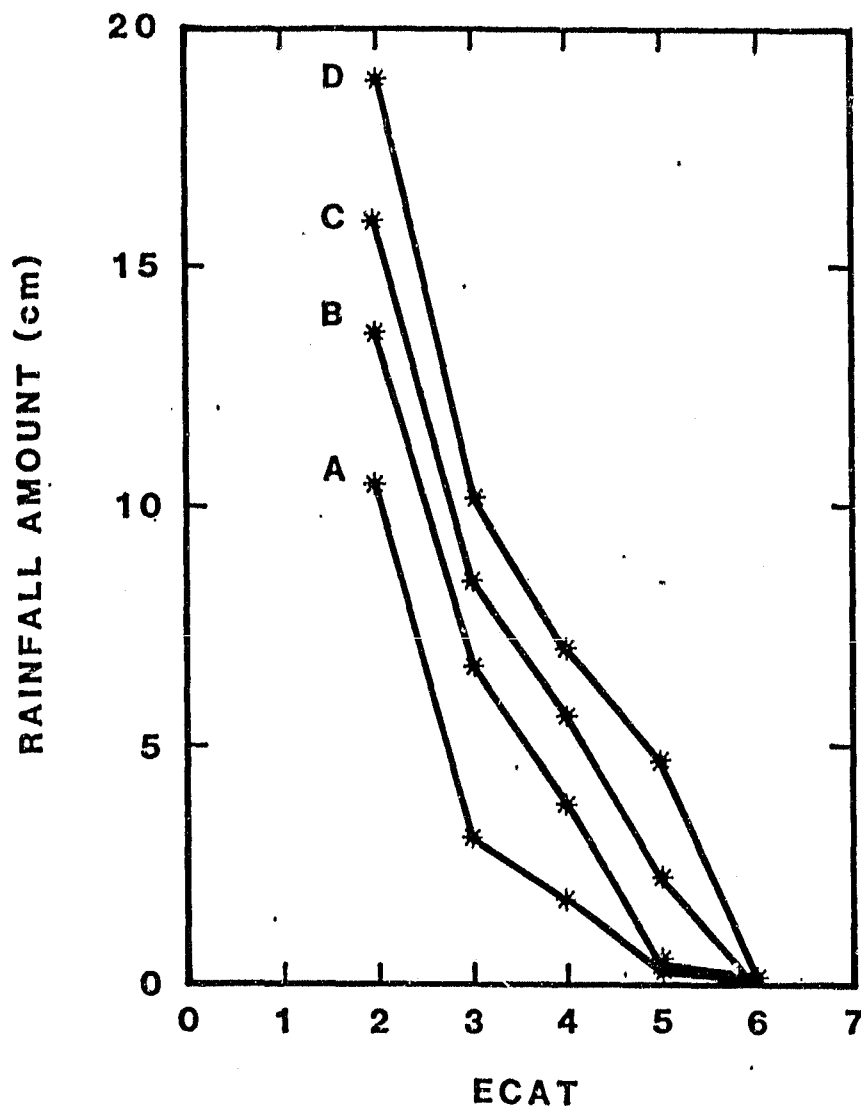
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This behavior extends throughout the series of figures, giving the capability to detect extended periods of dry conditions. For instance, Figure 9, the distribution of RAIN20 by ECAT20, indicates that a day with $ECAT20 = 5$ (min 21-day emissivity between 0.87 and 0.90) has a 90% probability of being associated with a 21-day rainfall of no more than 6 cm.

The statistical behavior expressed in these curves can be understood from the physics of soil moisture. As shown in the time series plots, Figures 2 through 5, each rainfall event diminishes the emissivity of the emitting layer by an amount proportional to the effective precipitation. The soil then undergoes relatively slow stage 1 drying for summer days with a correspondingly slow emissivity increase, followed by faster stage 2 drying with rapid return to the original emissivity. The length of stage 1 drying makes these changes detectable, even with ESMR's irregular observation frequency. In general, then, the emissivity alternates between a dry surface condition at about 0.92-0.94, and moister conditions with lower emissivities indicative of rainfall amount. Superimposed on this behavior is a random noise component resulting from irregularities in observation frequency, soil type, crop development stage, system noise, unaccounted meteorological effects, etc. Even with this high-amplitude noise, if the lowest emissivity in a given period is sufficiently high, it can be concluded that rainfall during the period was very low. With decreasing minimum emissivity, the estimate of total rainfall must increase.

These relationships have been summarized in Figure 10, which shows the 75% confidence level for precipitation in any of several

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- A RAIN 5,GIVEN ECAT 5
- B RAIN 10,GIVEN ECAT 10
- C RAIN 15,GIVEN ECAT 15
- D RAIN 20,GIVEN ECAT 20

Figure 10. 75% Confidence Level for Total Rain in Period, Given Emissivity Category (ECAT) of Lowest Emissivity.

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periods, given the minimum emissivity of the period. For instance, a minimum emissivity of 0.88 for any 21-day period ($ECAT20 = 5$) indicates, with 75% confidence, that rainfall ($RAIN20$) in the same period was no more than 4.7 cm. Figure 10 can, thus, be used to identify periods of low rainfall.

CLASSIFICATION BY DISCRIMINANT ANALYSIS

Passive microwave data were used in discriminant models to classify the moisture conditions in wheat croplands. Three elements are required: an objective set of moisture categories defined by ground truth data, one or more remotely sensed variables characteristic of each moisture category, and a method of analysis by which to relate the two. The method of discriminant analysis was used successfully.

Moisture Categories

Two methods of categorization were employed. In the first, categories were defined by API:

<u>APICAT</u>	<u>Definition</u>
1	$API \leq 1.0 \text{ cm}$
2	$1.0 \text{ cm} < API \leq 2.5 \text{ cm}$
3	$2.5 \text{ cm} < API$

This system was used only for the months of March, April and May.

In the second system, moisture categories were defined by total precipitation amounts received over the three-week period ending on the day of the observation. To examine the effect of the number of categories used, three levels of detail were analyzed.

<u>RAINCAT1</u>	<u>Definition</u>
1	$Rain = 0 \text{ cm}$
2	$0 \text{ cm} < Rain \leq 1 \text{ cm}$
3	$1 \text{ cm} < Rain \leq 5 \text{ cm}$
4	$5 \text{ cm} < Rain$

<u>RAINCAT2</u>	<u>Definition</u>
1	Rain = 0 cm
2	0 cm < Rain < 1 cm
3	1 cm < Rain < 5 cm
4	5 cm < Rain < 15 cm
5	15 cm < Rain

<u>RAINCAT3</u>	<u>Definition</u>
1	Rain = 0 cm
2	0 cm < Rain \leq 1 cm
3	1 cm < Rain \leq 3 cm
4	3 cm < Rain \leq 5 cm
5	5 cm < Rain \leq 10 cm
6	10 cm < Rain \leq 15 cm
7	15 cm < Rain \leq 20 cm
8	20 cm < Rain

These RAINCAT systems were used for each of the four seasons defined as:

<u>SEASON</u>	<u>MONTHS</u>
1	Feb-Mar-Apr
2	May-Jun-Jul
3	Aug-Sep-Oct
4	Nov-Dec-Jan

Classification Variables

The following variables were used:

<u>VARIABLE</u>	<u>DEFINITION</u>
EMIS0	Emissivity on day of observation
EMIS5	Average emissivity for 1st through 5th days before observation.
EMIS10	Average emissivity for 6th through 10th days before observation.
EMIS15	Average emissivity for 11th through 15th days before observation.
EMIS20	Average emissivity for 16th through 20th days before observation.

EMIS0 was used as the single classifying variable in the APICAT study. All five variables were used in the RAINCAT classifications.

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Two additional analyses were performed, to evaluate the utility of restricted variable sets. These analyses were motivated by the method's handling of missing data for the RAINCAT3 analysis. For example, a 5-day break in the ESMR emissivity data might result in, say, EMIS 5 being undefined while the other four variables were available for analysis. In this case, the discriminant analysis would simply ignore the entire observation vector. On the other hand, a separate discriminant analysis could be performed, using all of the variables except EMIS5. To examine the effect of restricted variable sets, the following analyses were performed, using the same categories as in RAINCAT3:

RAINCAT4 Variables: EMIS0, EMIS5, EMIS10

RAINCAT5 Variables: EMIS0, EMIS10, EMIS15, EMIS20

Analysis Method

The theory of discriminant analysis is presented in such texts as Kendall and Stuart (1976) and Rao (1965). The method has been implemented in the Statistical Analysis System (SAS) as Procedure DISCRIM (SAS Institute Inc., 1979). SAS is a software package available on the AMDAHL 470 computer system. Inputs to the DISCRIM procedure are observations of classification variables and related true categories determined from ground truth data. The DISCRIM procedure in SAS develops a system of probabilistic discriminant functions. It applies these functions against the input data set and prepares a summary of their performance in classifying observations into categories. Optionally, SAS can store these functions for later use in classifying independent data sets.

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DISCRIM works by assuming that the observation vectors from each category are samples from distinct multivariate normal populations. For category t of n categories, it calculates a mean n -dimensional observation vector \bar{x}_t . It then computes a set of generalized squared distance functions, $D_t^2(x)$, characterizing the separation in n -space of each vector x from \bar{x}_t . The form of the distance function depends upon the homogeneity of the m within-groups covariance matrices, and upon the assumed prior probabilities. If the several within-category populations can be assumed to share a common covariance matrix, it is estimated by a pooled covariance matrix S , computed from all of the observations. If this assumption is not made, separate within-groups covariance matrices, S_t , are computed. DISCRIM also has an optional test of the covariance homogeneity hypothesis. The distance function has the linear form:

$$D_t^2(x) = g_1(x,t) + g_2(x,t)$$

where

$$g_1(x,t) = (x - \bar{x}_t)' S_t^{-1} (x - \bar{x}_t) + \ln |S_t|$$

if within group covariance matrices are used.

$$g_1(x,t) = (x - \bar{x}_r)' S^{-1} (x - \bar{x}_t) \text{ otherwise.}$$

$$g_2(x,t) = -2 \ln (\text{prior probability for group } t),$$

if prior probabilities are not assumed equal.

$$g_2(x,t) = 0 \text{ otherwise.}$$

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The classification procedure, then, is to assign each observation to group u if $D_t^2(x)$ is a minimum for $t=u$. DISCRIM takes this process one step further, by using the assumption of multivariate normality to compute posterior probabilities for membership in each of the m categories. These probabilities are given by

$$P(j|x) = \exp[-\frac{1}{2}D_j^2(x)] / \sum_{k=1}^m \exp[-\frac{1}{2}D_k^2(x)]$$

From this probability information, a user can decide how much confidence to place in the system's classification of an observation. Table 9 is an example of DISCRIM's output listing of classifications and posterior probabilities for a calibration data set. Errors in classification are flagged by an asterisk.

Prior Probabilities

The discriminant method requires estimation of the prior probability of each category; that is, the assumed probability that an event will fall in a given category, based on all that is known prior to acquisition of the values of the classification variables. DISCRIM can use any set of assumed prior probabilities, but two such sets were used. One results from the assumption that, until current remotely sensed input data are available, the probability of each category is equal to that of any other category. This option will be referred to as "equal priors". The other, perhaps more reasonable assumption would be that prior probabilities are equal to the observed relative frequencies of the categories. This option is referred to as "proportional priors".

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Table 10 Example of Output from DISCRIM Procedure

PROPORTIONAL PRIOR PROBABILITIES A=10					
CLASSIFICATION RESULTS FOR CALIBRATION DATA					
POSTERIOR PROBABILITY OF MEMBERSHIP IN MOISTCAT:					
ID	FROM MOISTCAT	CLASSIFIED INTO MOISTCAT	1	2	3
255741	1	1	0.8475	0.1481	0.0054
255743	1	1	0.8233	0.3259	0.0530
255744	1	1	0.4085	0.1784	0.0121
255746	2	1	0.8596	0.2973	0.0431
255750	3	3	0.0131	0.3835	0.8033
255285	2	1	0.4788	0.4204	0.1031
255287	2	1	0.8584	0.1387	0.0049
255288	1	1	0.8000	0.1886	0.0134
255300	1	1	0.4944	0.4086	0.0960
255301	1	1	0.7778	0.2049	0.0172
255302	1	1	0.8373	0.3157	0.0490
255304	3	3	0.0258	0.4355	0.8385
255308	2	2	0.0971	0.5288	0.3772
255309	2	2	0.1041	0.5288	0.3871
255311	1	2	0.3854	0.4805	0.1541
255313	1	1	0.7462	0.2308	0.0232
255314	1	1	0.8863	0.2788	0.0358
255322	1	1	0.7238	0.2444	0.0278
255323	1	1	0.7489	0.2284	0.0227
255325	1	1	0.7837	0.1918	0.0145
255329	1	1	0.8582	0.1287	0.0052
255340	1	1	0.8584	0.2823	0.0413
255342	1	1	0.7025	0.2849	0.0325
255344	1	1	0.7217	0.2421	0.0252
255345	1	1	0.8737	0.2888	0.0385
255346	1	1	0.8653	0.1309	0.0039
255347	1	1	0.8023	0.1847	0.0131
255348	1	1	0.8598	0.1355	0.0047
255351	1	1	0.8717	0.2883	0.0400
255352	1	1	0.8297	0.1615	0.0069
255353	1	1	0.8581	0.1370	0.0049
255354	1	1	0.8266	0.1641	0.0093
255355	1	1	0.8683	0.1284	0.0033
255358	1	1	0.8138	0.1749	0.0112
255359	1	1	0.8495	0.1444	0.0061
255361	1	1	0.7917	0.1935	0.0148
255363	1	1	0.8290	0.1620	0.0090
255365	1	1	0.8081	0.3345	0.0574
255366	1	1	0.8556	0.1392	0.0053
255368	1	1	0.8418	0.1512	0.0072
255371	1	1	0.8693	0.1285	0.0021
255372	1	1	0.8342	0.1578	0.0082
255373	1	1	0.7878	0.2133	0.0191
255375	1	1	0.8544	0.1402	0.0054
255377	2	1	0.8150	0.1739	0.0111
255378	2	1	0.2046	0.1827	0.0127
255379	3	1	0.6881	0.1285	0.0034
255382	2	1	0.7186	0.2624	0.0290
255384	2	1	0.8125	0.1781	0.0114
255385	1	1	0.8295	0.1518	0.0089

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Procedure

Analyses were performed for grid cell data representing 25 km resolution elements and for spatially averaged data representing simulated resolution of about 50 km. These data types are denoted, respectively, by "AV = 0" and "AV = 1".

The APICAT analysis was performed for each of the four combinations of averaged/unaveraged data and equal/proportional prior probabilities; and the period of study was the months of March through May of 1974 and 1975. The RAINCAT analyses were performed for all combinations of season number and equal/proportional priors, but only the non-averaged data set was used. In each case, days with snowcover were allowed to remain in the data.

In every analysis, the covariance homogeneity test rejected (at $\alpha = 0.10$) the hypothesis of homogeneity. Thus, individual within-groups covariance matrices were computed.

Results

Three measures of effectiveness were used to evaluate the various analyses. Prefigurance (PF) and Post Agreement (PA) (AWS, 1978) measure the conditional probability of a correct classification given, respectively, the observed category or the classified category. For instance, suppose category 1 occurs 10 times, 20 observations are classified as category 1, and only 5 of those classifications are correct. The prefigurance for category 1 is $5/10 = 50\%$. The post agreement for category 1 is $5/20 = 25\%$. Each category, then, has both a PF and a PA score. Appendices C and D give prefigurance and post agreement results for each analysis in a relative frequency matrix.

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The individual category PF or PA scores are the numbers on the diagonals of the matrices. An overall PA or PF score can be defined for each matrix by taking the simple average of all defined scores for that matrix. For example, if a 5 x 5 matrix has one undefined diagonal entry, and four defined PF scores, then

$$\overline{PF} = \frac{1}{4} \sum_{i=1}^4 PF_i$$

This average score must be used with caution, since it gives undue weight to individual scores from categories with low frequencies of occurrence. Nevertheless, mean prefigurative and postagreement scores can be used to compare the performance of different models.

The third measure of classification effectiveness is simply the relative frequency of correct classifications, denoted "%COR". This measure and both \overline{PF} and \overline{PA} are given in Table 10 for each analysis.

Discussion

These summary figures for the APICAT analyses show no appreciable difference between results for averaged and nonaveraged data. This result will be important to the SMMR phase of this project, as it demonstrates that reduced resolutions have little effect on classification accuracy.

A second observation is that, for all analyses, the assumption of proportional prior probabilities results in better total percent correct (%COR) as well as better mean post agreement (\overline{PA}). By contrast the assumption of equal priors gave equal or, usually, better

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Table 11. Performance Summary

APICAT (Mar-Apr-May)	%COR	\overline{PF}	\overline{PA}	N
AV = 0, PE*	62	58	54	2165
AV = 0, PP**	65	53	60	2165
AV = 1, PE	62	58	53	2228
AV = 1, PP	64	51	58	2228

RAINCAT1 (AV = 0)	%COR	\overline{PF}	\overline{PA}	N
Season 1, PE	36	46	41	1308
PP	59	39	53	1308
Season 2, PE	64	65	59	769
PP	74	65	70	769
Season 3, PE	65	76	64	1330
PP	70	76	69	1330
Season 4, PE	47	58	48	1818
PP	55	47	56	1818

RAINCAT2 (AV = 0)	%COR	\overline{PF}	\overline{PA}	N
Season 1, PE	32	52	34	1308
PP	59	36	54	1308
Season 2, PE	56	68	48	769
PP	72	54	77	769
Season 3, PE	53	69	55	1330
PP	63	67	67	1330
Season 4, PE	44	59	39	1818
PP	54	39	52	1818

Continued

*PE - Priors equal

**PP - Priors proportional

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Table 11. Continued

RAINCAT3 (AV = 0)	%COR	PF	PA	N
Season 1, PE	29	36	29	1308
PP	49	22	42	1308
Season 2, PE	39	44	40	769
PP	55	35	55	769
Season 3, PE	36	50	39	1330
PP	47	48	50	1330
Season 4, PE	34	58	37	1818
PP	48	40	55	1818

RAINCAT4 (AV = 0)	%COR	PF	PA	N
Season 1, PE	27	41	22	1645
PP	42	27	39	1645
Season 2, PE	32	38	34	928
PP	49	25	45	928
Season 3, PE	25	41	25	1629
PP	40	28	35	1629
Season 4, PE	29	48	29	2052
PP	48	25	43	2052

RAINCAT5 (AV = 0)	%COR	PF	PA	N
Season 1, PE	24	55	30	1362
PP	47	32	63	1362
Season 2, PE	32	38	33	769
PP	52	29	58	769
Season 3, PE	33	48	33	1357
PP	45	38	50	1357
Season 4, PE	32	55	32	1899
PP	46	33	47	1899

SUMMARY

This research was conducted to examine the potential of the use of short wavelength information from passive microwave radiometers on earth satellites. The Electrically Scanning Microwave Radiometer (ESMR) 1.55 cm passive microwave radiation, expressed as a brightness temperature, was converted to emissivity for 25 cm grid cells for September 5, 1973 to May 30, 1975 for the Southern Great Plains. The frequency of coverage was on the order of once every two or three days for the majority of the period for the eastern two-thirds of Kansas and Oklahoma and northwest Texas. Daily estimates of air temperature, precipitation, and snow cover were also available for the grid cells. Correlations of these emissivities showed the following results:

1. ESMR emissivities were highly correlated with an antecedent precipitation index (API) used to infer the moisture content of the upper layer of the soil. Correlations were highest in the grid cells with high percentages of winter wheat in the fall at planting time.

2. Temporal series of ESMR emissivity related well with crop calendar documentions of the progress of planting, the state of soil moisture at planting, and the occurrence of excessive moisture that necessitated replanting.

3. Case study analyses of emissivity identified periods of frozen soils, as inferred from air temperature records. The possibility of winter kill detection or early warning is suggested.

4. Emissivities for fully developed winter wheat crop canopies in April and May correlated well with adequacy of crop moisture, as indicated by rainfall reports and yield tabulations. Crop canopies in

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a fully-watered state were lower (0.897) than canopies under stress (0.930). Small standard deviations indicate the significance of the small variations.

5. The emissivities from thunderstorms in the grid area at the time of overpass were of the same range as emissivities for wet soil. Thus, the presence of thunderstorms will not significantly degrade the ability to monitor crop moisture with passive microwave data.

6. Observed emissivities from ESMR were very similar to the emissivities obtained from aircraft and truck measurements. This indicates the validity of approximating the temperature of the emitting layer with surface reports of air temperature.

7. Passive microwave sensors from space have all-weather, day or night utility.

8. The use of 1.55 cm passive microwave emissivities for early warning of crop condition assessment is strongly supported by the investigators.

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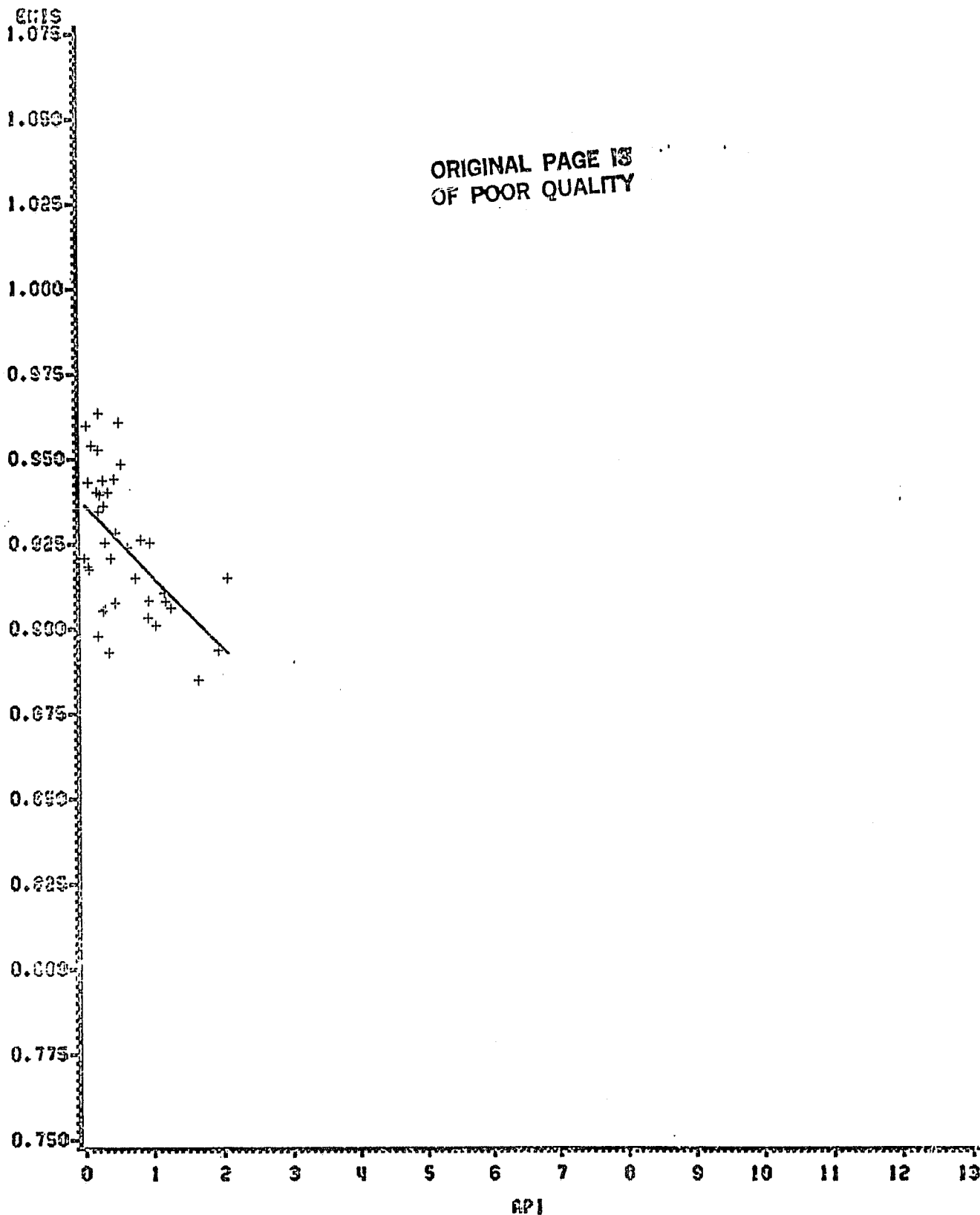
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APPENDIX A
SCATTER PLOTS OF EMISSIVITY AND API FOR
SELECTED GRID CELLS FOR EACH SEASON

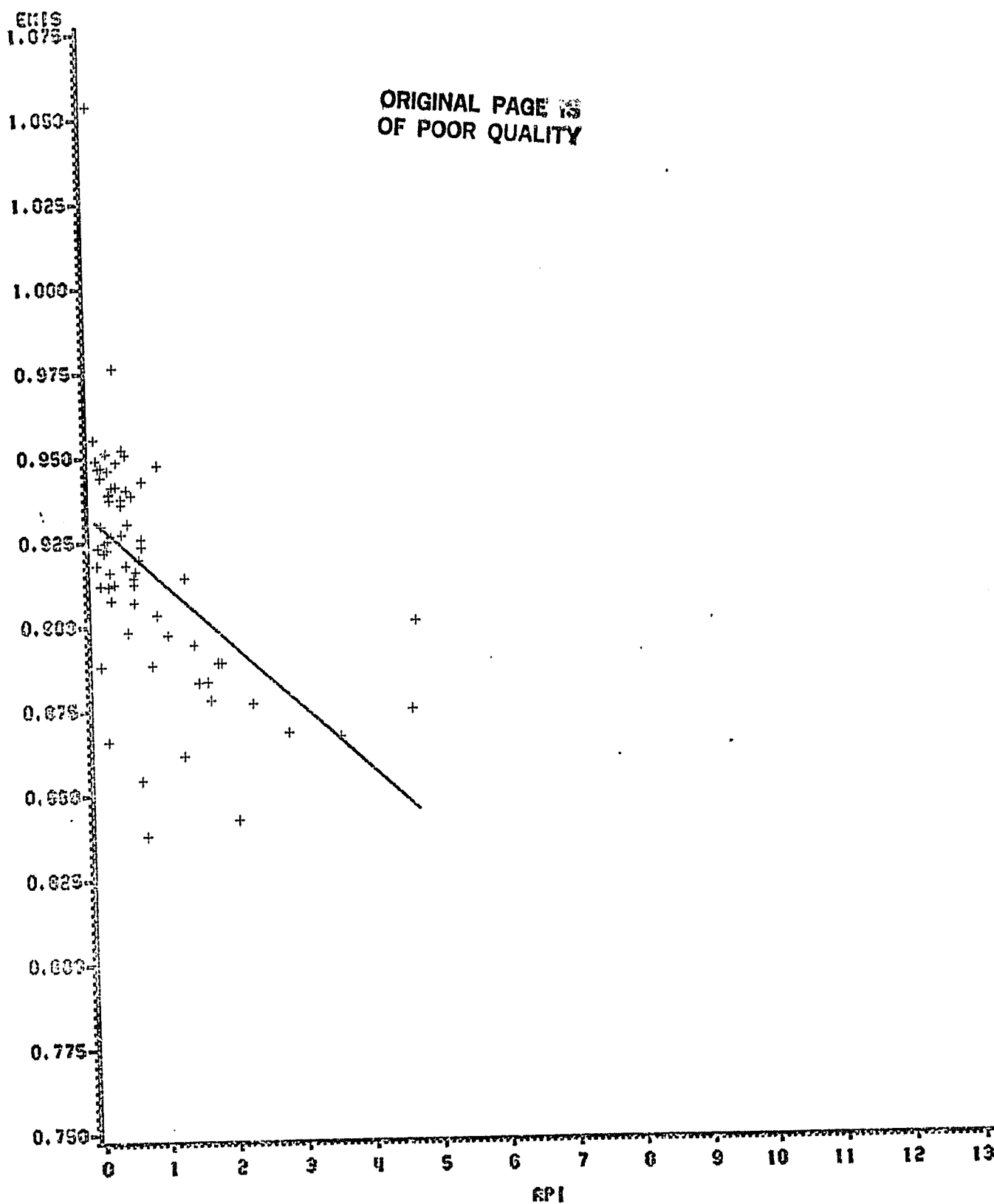
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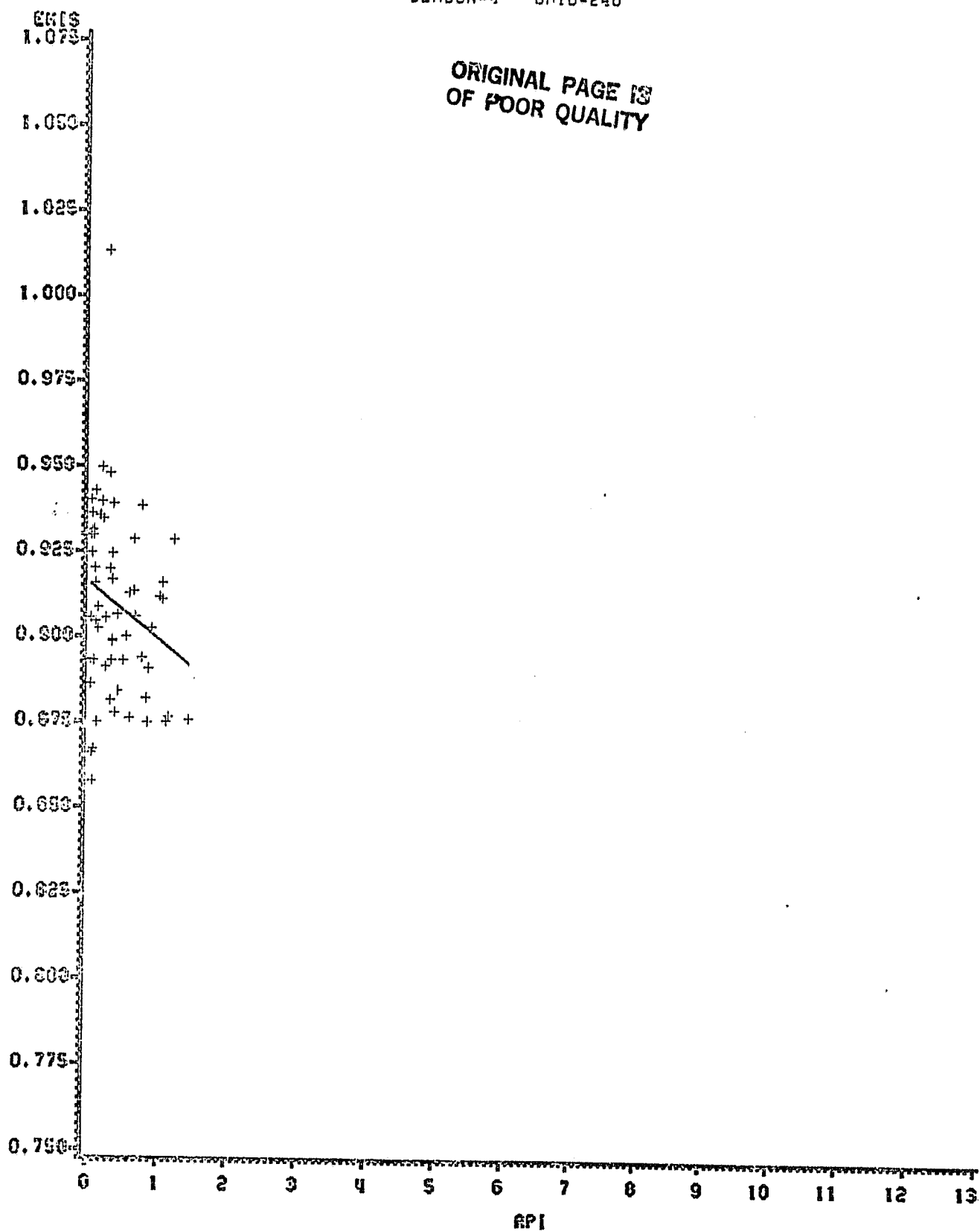
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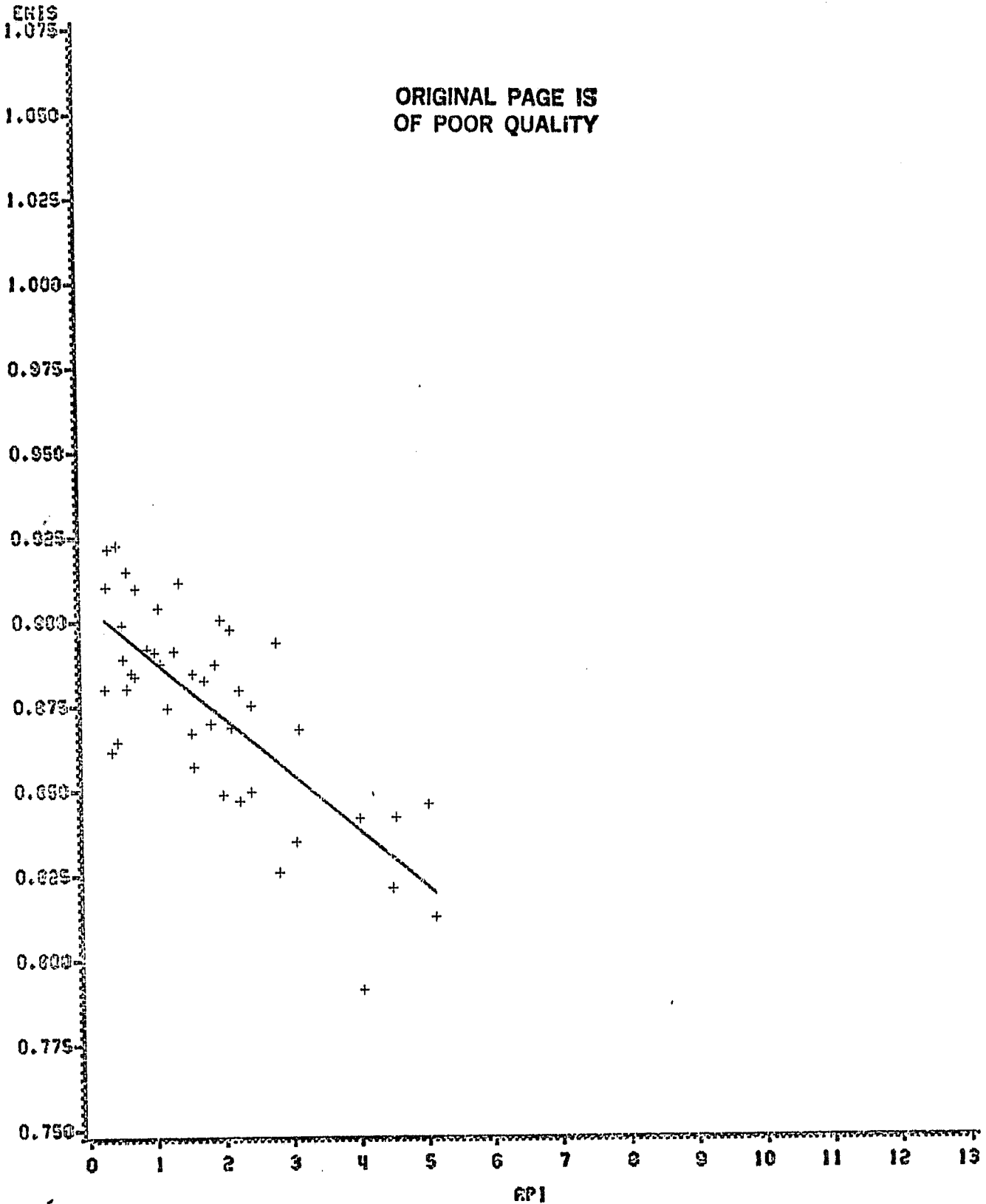
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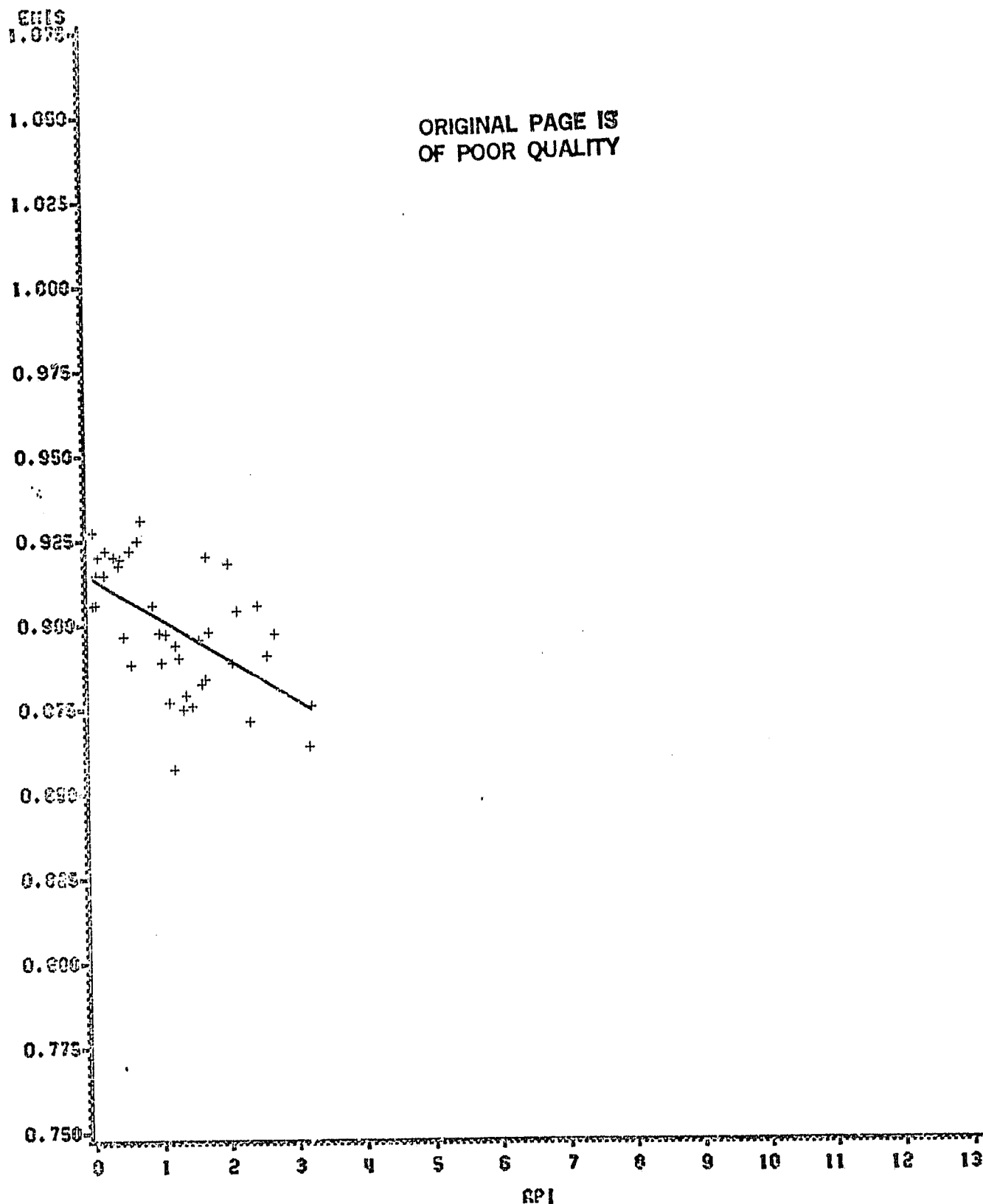
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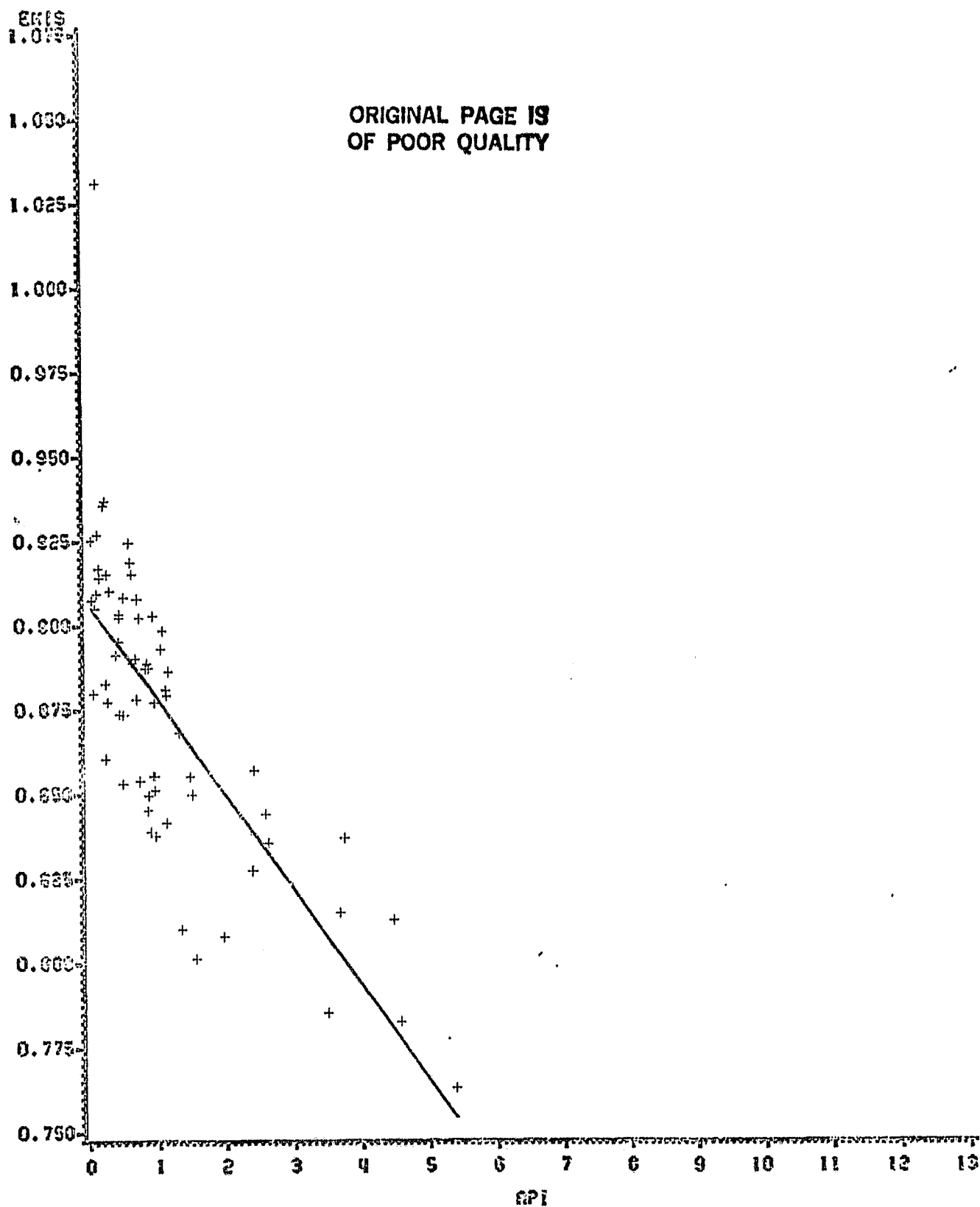
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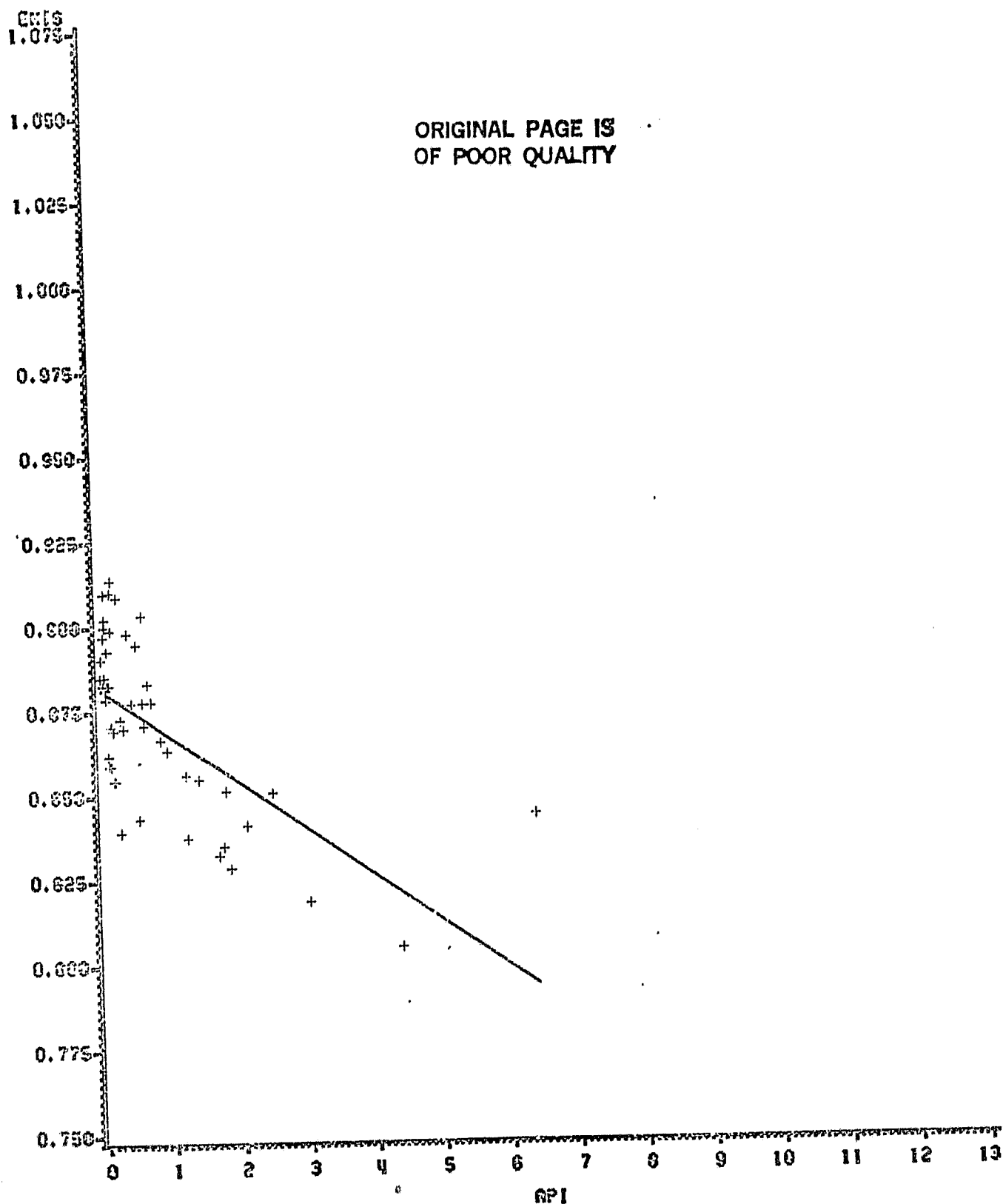
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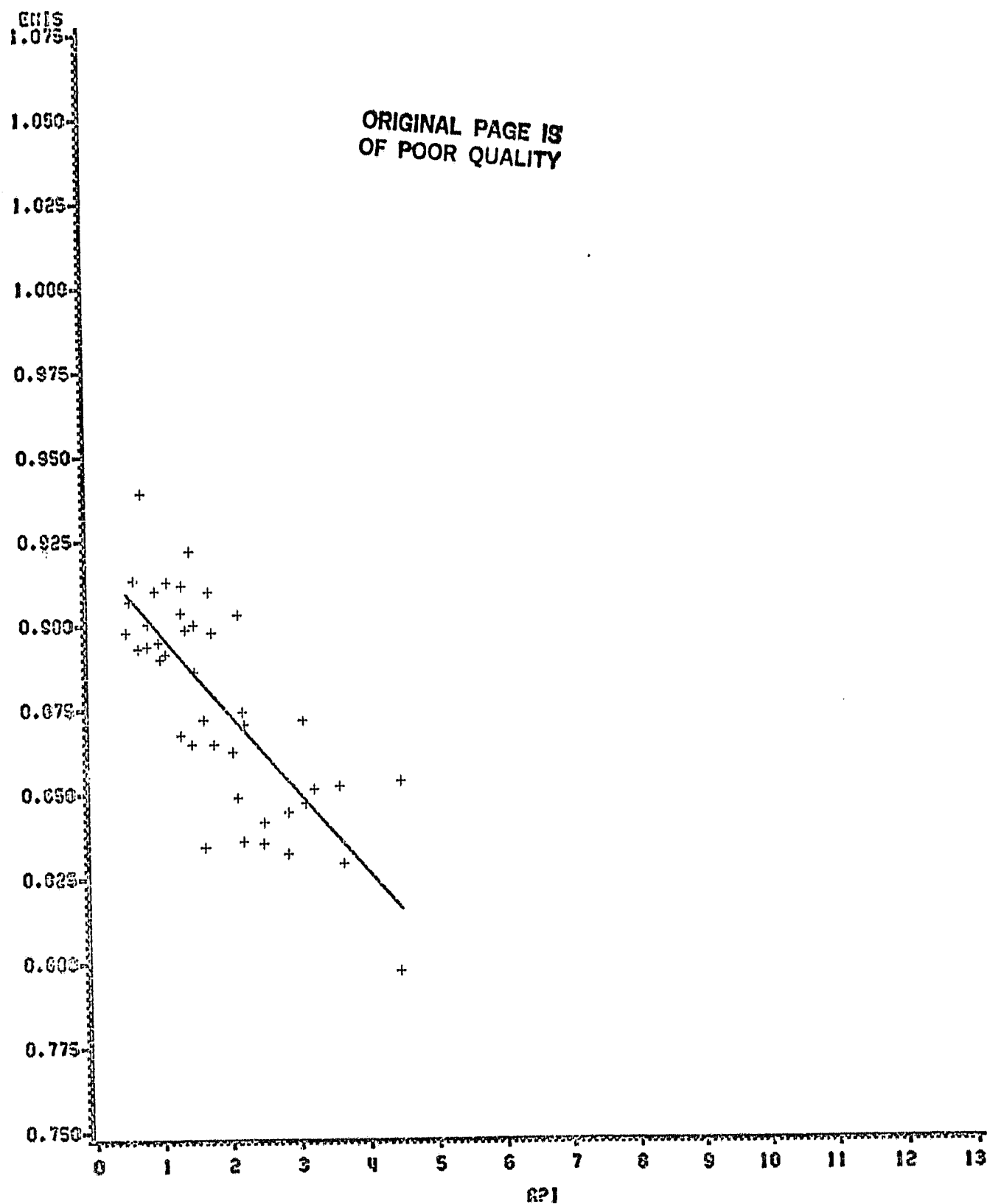
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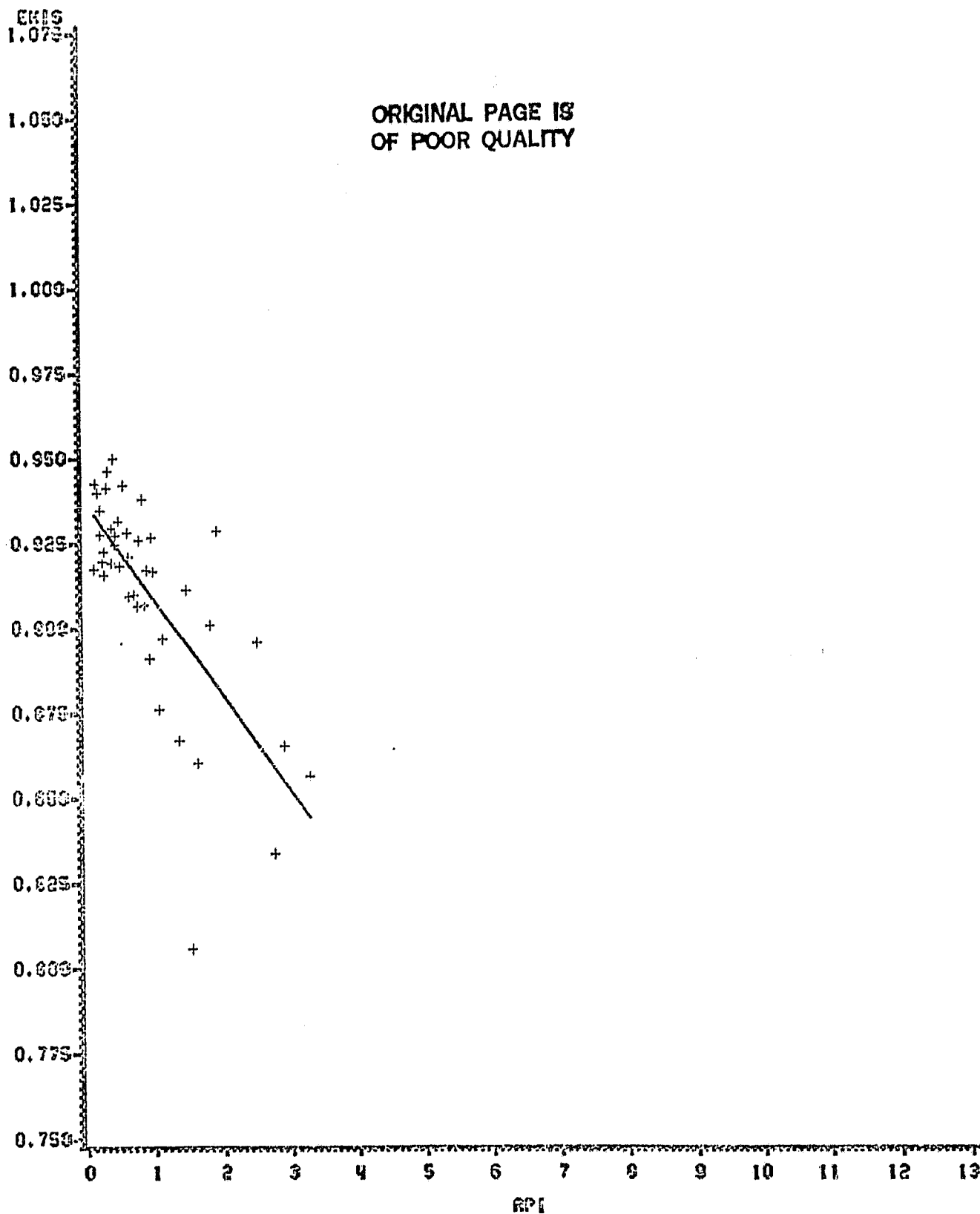
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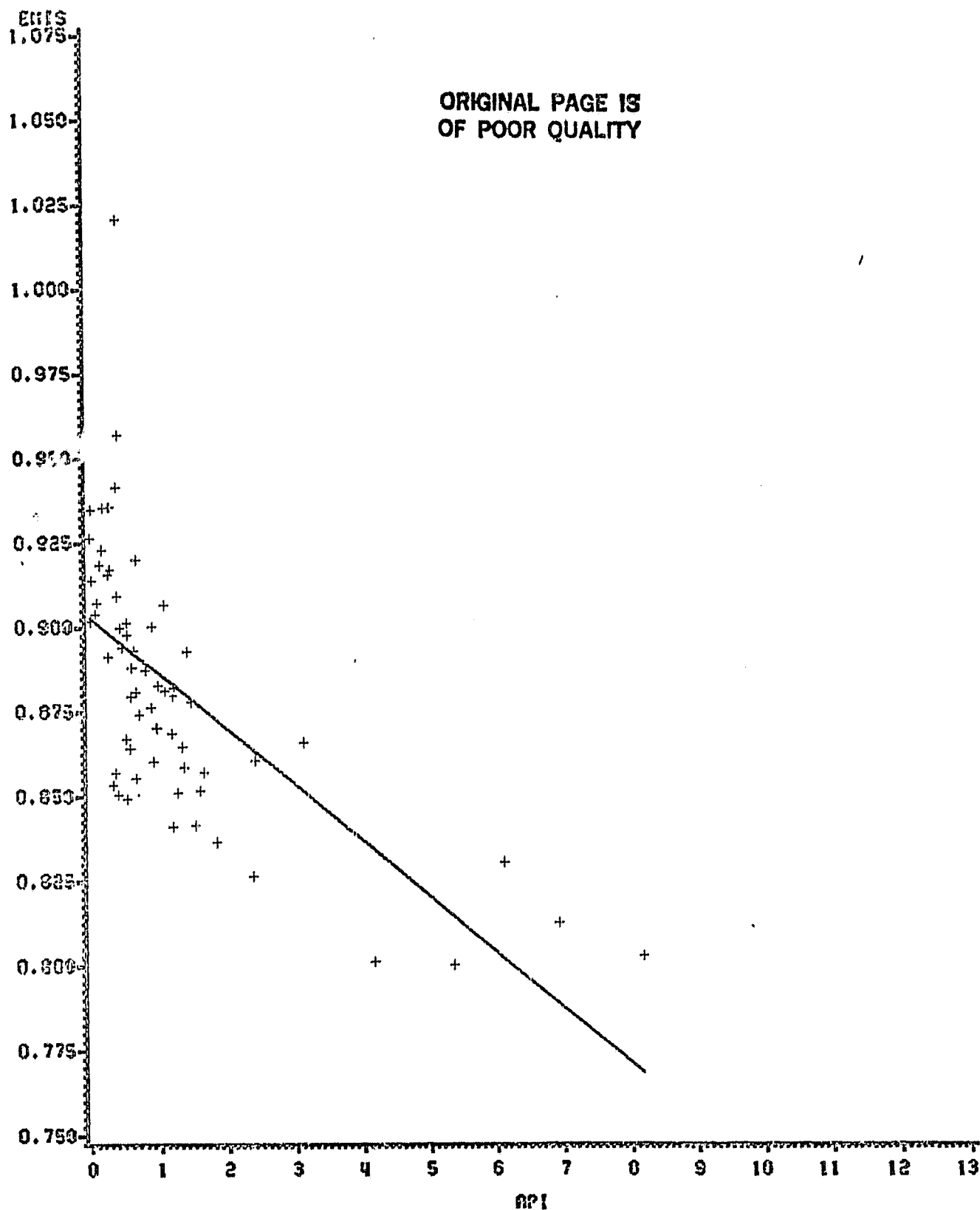
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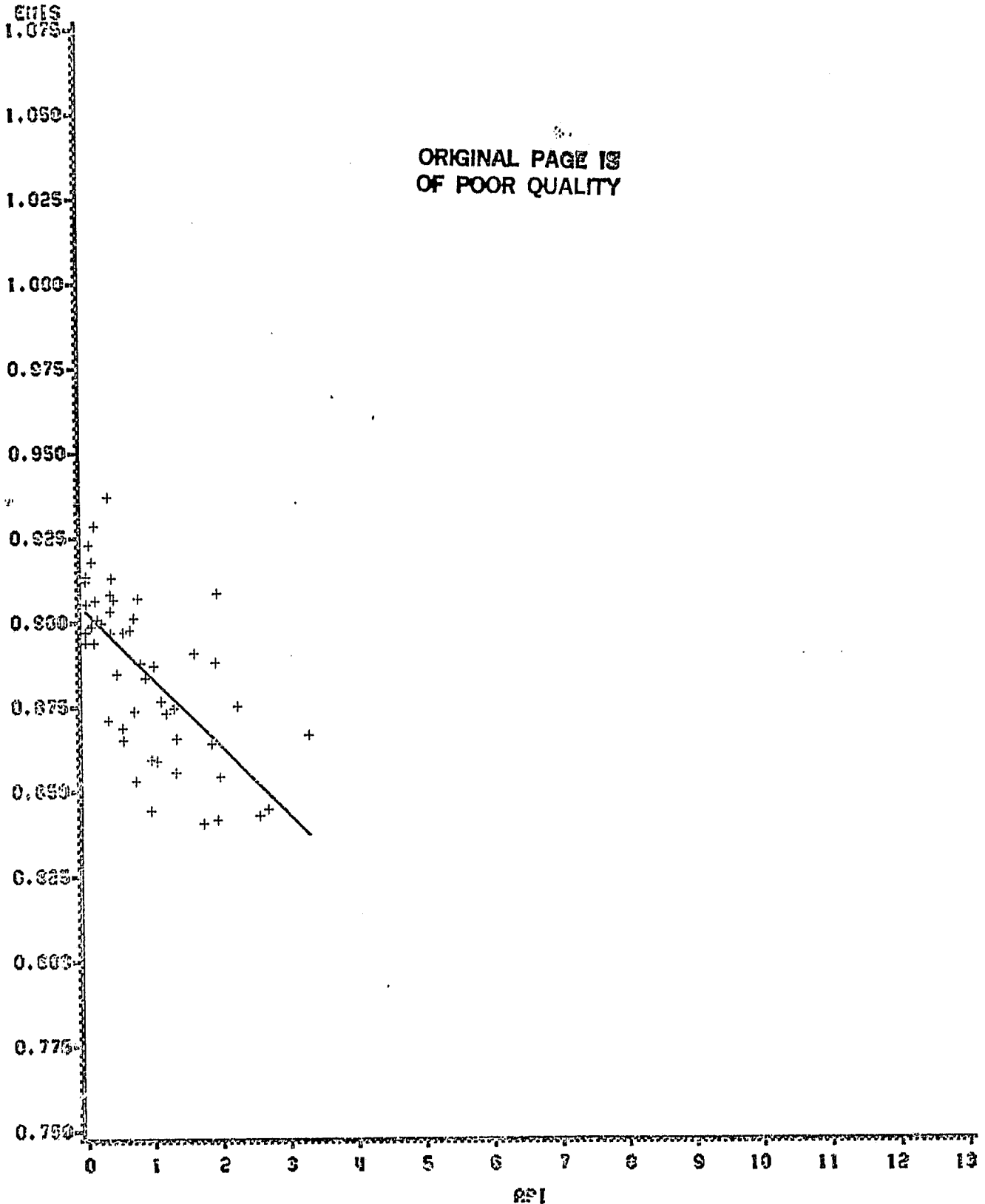
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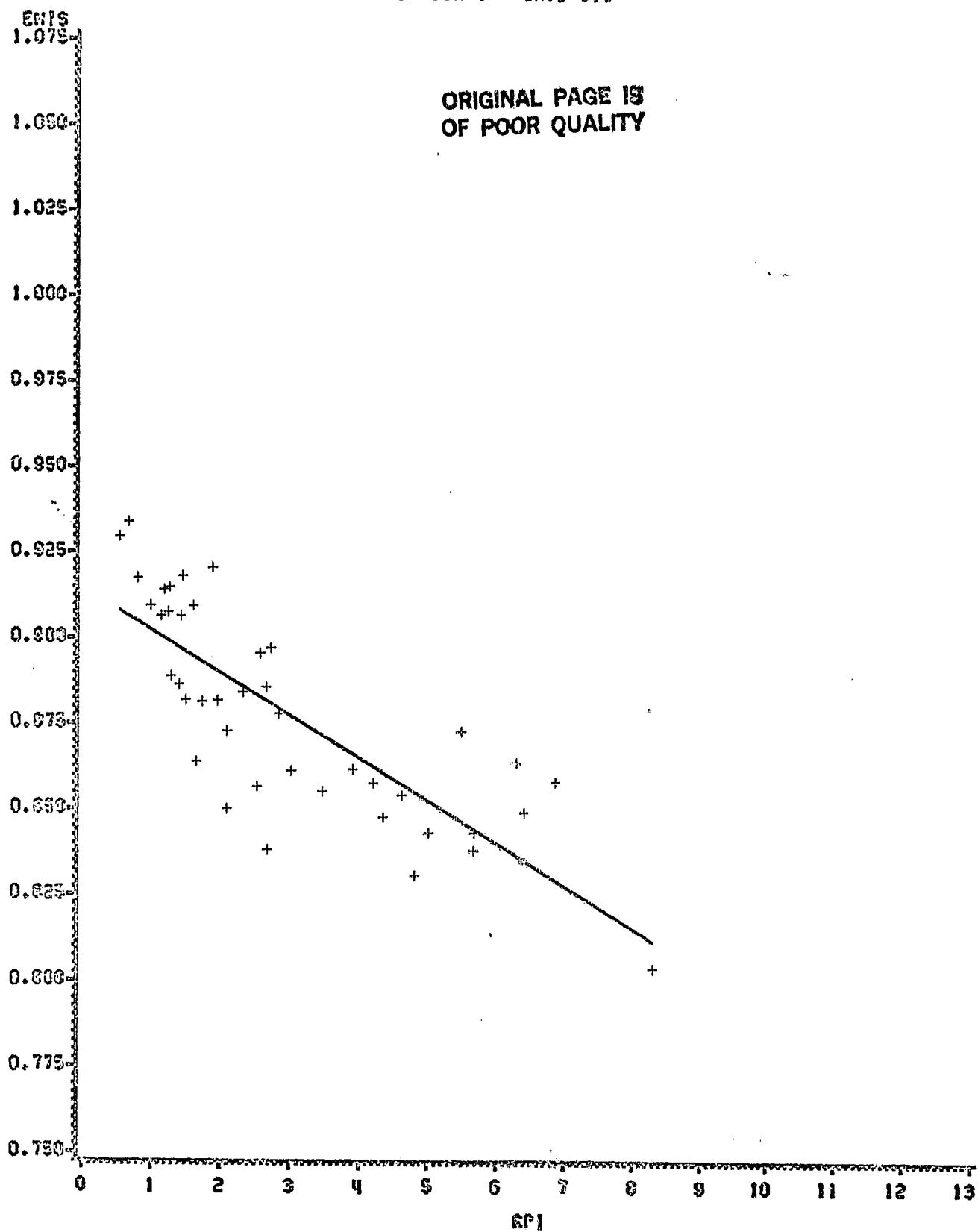
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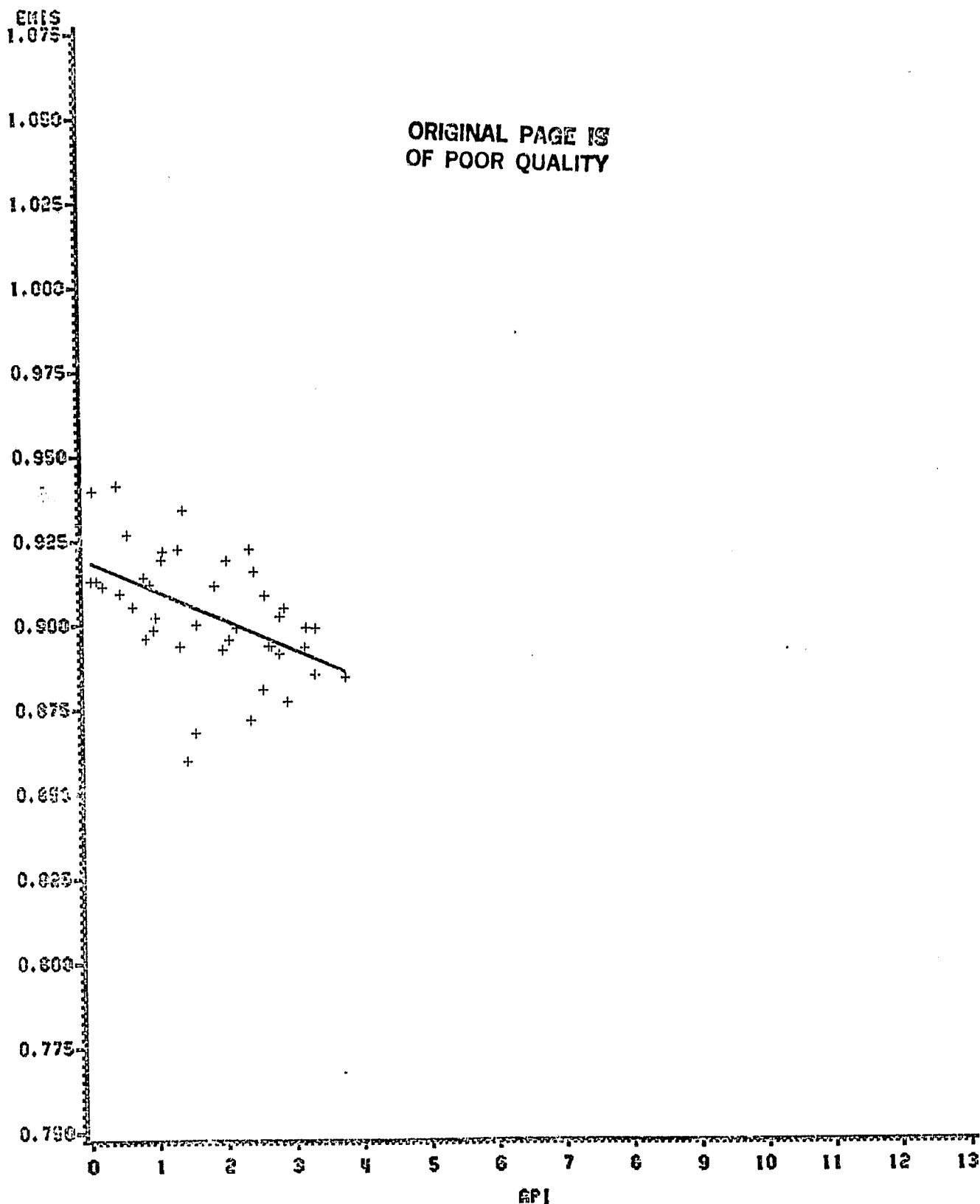
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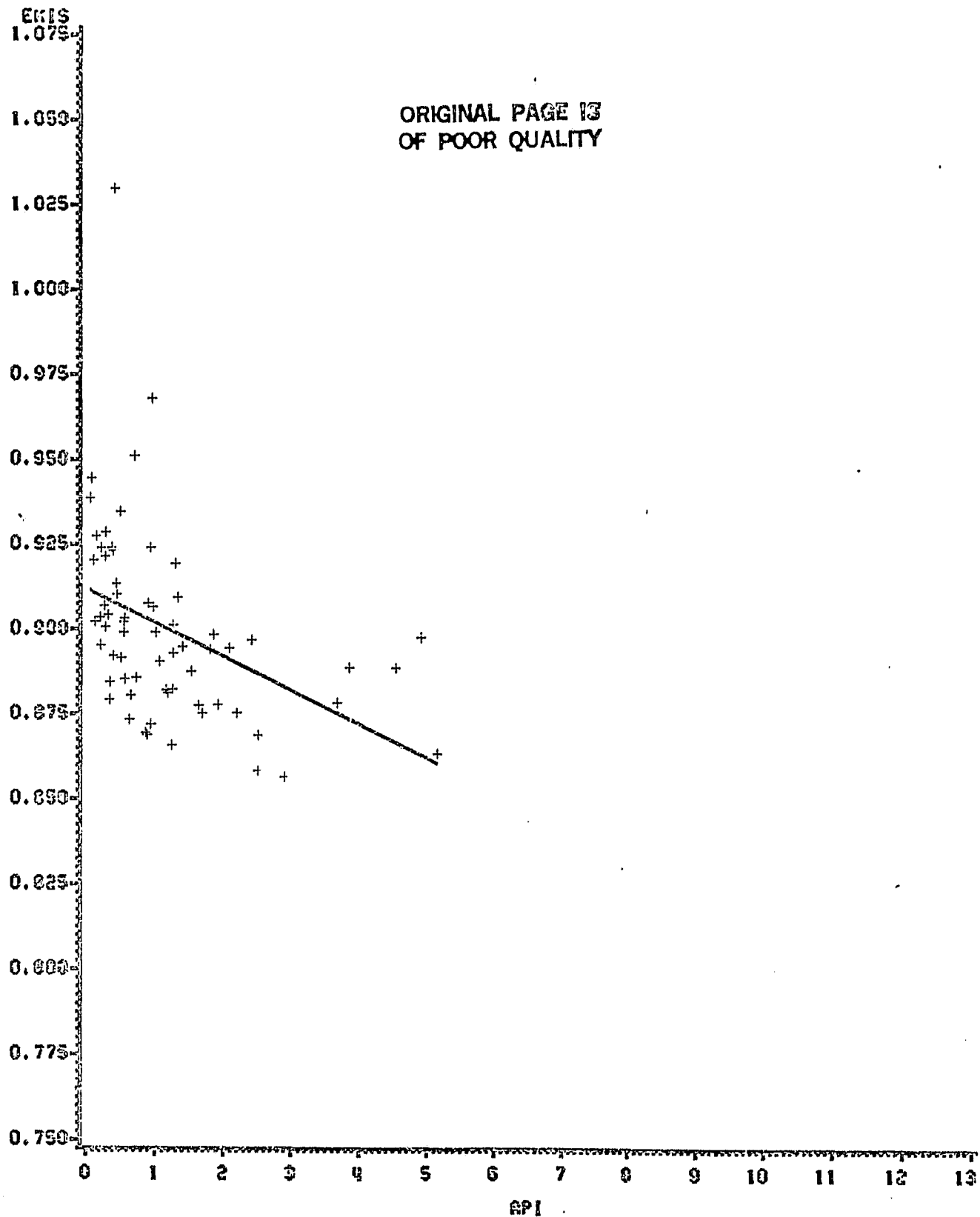
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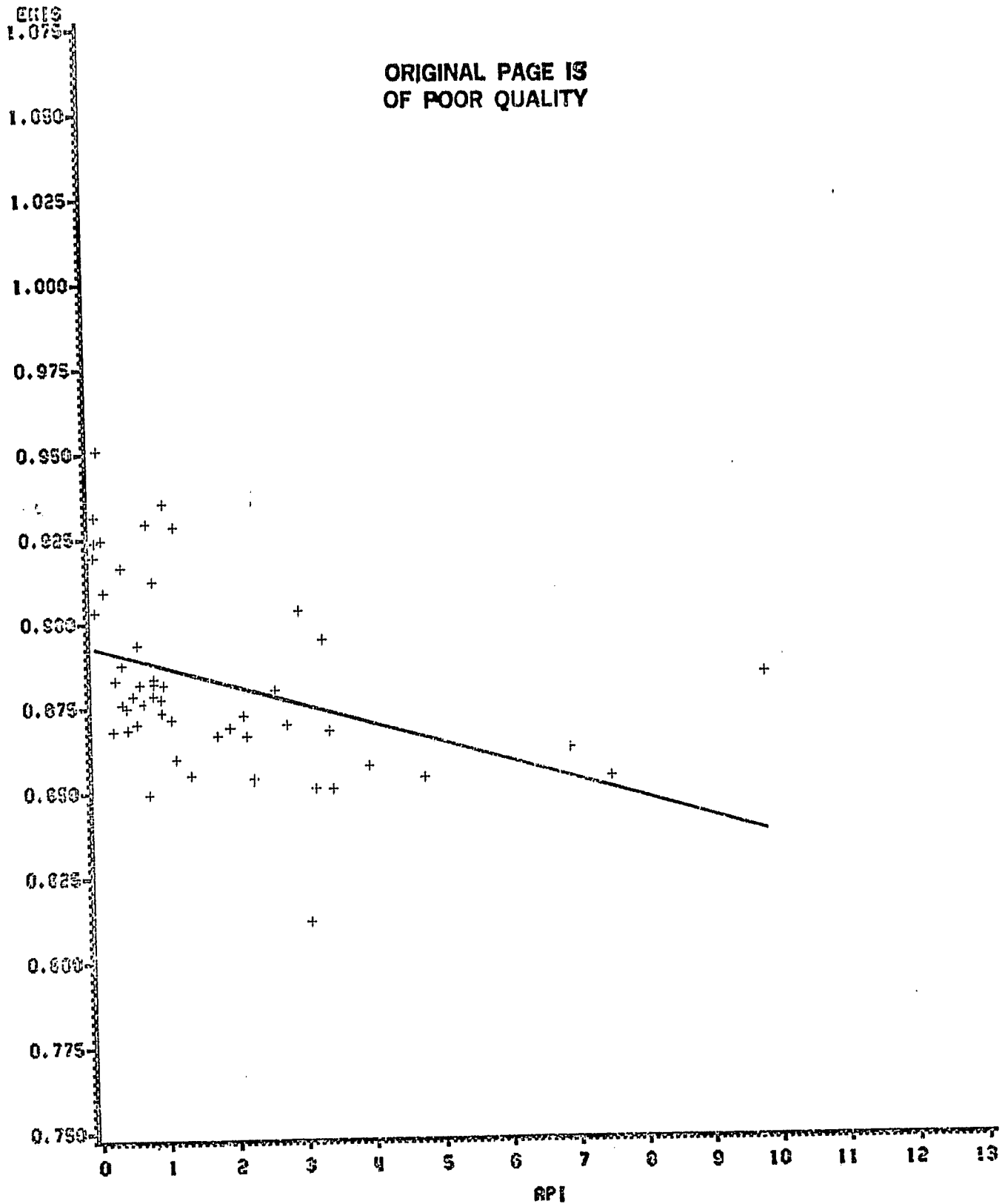
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SEASON=4 GRID=515



APPENDIX B
DISTRICT PRECIPITATION AVERAGES (CM) FOR
KANSAS AND OKLAHOMA FOR JUNE TO NOVEMBER 1973 AND 1974

KANSAS
District

Month

	NW			WC			SW			NC			C			SC		
	73	74	A	73	74	A	73	74	A	73	74	A	73	74	A	73	74	A
June	5.91	11.86	8.40	3.68	8.35	8.17	2.31	6.42	6.70	3.27	7.36	10.92	3.32	7.06	9.93	2.59	7.23	9.98
July	11.02	3.98	7.0	10.21	2.31	6.65	8.20	3.63	6.04	15.5	1.01	7.95	15.69	1.39	7.92	11.60	2.56	7.51
August	2.91	6.17	5.91	5.53	5.66	6.37	4.47	9.29	5.96	5.43	8.10	7.97	8.78	10.0	7.69	3.25	14.88	7.13
September	13.89	0.35	3.98	11.81	0.88	3.55	11.45	1.82	3.55	23.34	1.72	6.68	23.13	2.36	6.93	27.2	3.63	6.50
October	2.71	3.81	2.71	1.93	5.74	2.94	1.75	4.44	3.20	10.2	5.20	3.96	9.80	10.0	4.82	9.19	7.06	4.95
November	2.87	1.98	1.72	2.31	1.72	1.70	1.75	1.37	1.57	4.64	2.92	2.38	3.09	2.64	2.64	1.75	4.44	2.69

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OKLAHOMA
District

Month

	Panhandle			WC		SW		NC		C					
	73	74	A	73	74	A	73	74	A	73	74				
June	1.93	6.68	6.68	6.95	4.16	8.61	10.10	4.62	8.73	4.41	5.68	9.55	14.42	9.42	11.27
July	11.17	2.97	6.35	1.60	0.83	5.66	9.75	0.71	5.86	10.03	2.31	7.03	7.21	1.87	7.64
August	3.73	13.69	2.34	15.34	15.87	5.63	2.41	12.26	5.33	2.79	19.53	7.21	3.88	11.91	6.98
September	10.30	3.58	6.27	5.41	11.88	5.79	18.64	14.22	6.47	16.04	7.21	6.93	22.13	15.36	8.55
October	3.20	4.69	3.03	1.90	8.96	2.29	6.40	9.84	6.88	10.76	8.66	5.67	8.33	15.06	7.46
November	1.77	1.77	1.7	1.77	7.89	2.59	3.30	3.12	3.02	3.32	9.70	3.42	9.55	9.32	4.69

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APPENDIX C
PREFIGURANCE TABLES*

*Relative frequency of actual category (from ground truth), given the category into which observations were classified. If the actual category is a and the classified category is c , these tables give approximations of the conditional probabilities, $P(c|a)$. Prefigurance, for any category, is the entry on the diagonal.

PREFIGURANCE TABLES

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APICAT

AV = 0 EQUAL PRIORS				
OBS CAT	% CLASSIFIED IN CAT			N
	1	2	3	
1	80	14	6	1198
2	41	28	30	696
3	58	20	21	271
				2165

APICAT

AV = 1 EQUAL PRIORS				
OBS CAT	% CLASSIFIED IN CAT			N
	1	2	3	
1	81	13	5	1241
2	43	26	31	718
3	60	19	21	269
				2228

APICAT

AV = 0 PROPORATIONAL PRIORS				
OBS CAT	% CLASSIFIED IN CAT			N
	1	2	3	
1	90	10	1	1198
2	58	34	8	696
3	22	44	34	271
				2165

APICAT

AV = 1 PROPORTIONAL PRIORS				
OBS CAT	% CLASSIFIED IN CAT			N
	1	2	3	
1	89	10	1	1241
2	59	33	8	718
3	21	46	32	269
				2228

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PREFIGURANCE TABLES

RAINCAT 1

SEASON = 1

PRIORS EQUAL

	1	2	3	4	N
1	68	23	6	3	66
2	51	36	7	6	486
3	25	17	27	31	593
4	15	11	21	53	163
					1308

PRIORS PROPORTIONAL

	1	2	3	4	N
1	0	85	16	2	66
2	0	83	16	1	486
3	0	37	59	4	593
4	0	26	62	12	163
					1308

PREFIGURANCE TABLES

RAINCAT 1

SEASON = 2

PRIORS EQUAL

	1	2	3	4	N
1	-	-	-	-	0
2	0	76	22	2	90
3	0	41	40	19	290
4	0	3	17	80	389
					769

PRIORS PROPORTIONAL

	1	2	3	4	N
1	0	0	0	0	0
2	0	38	59	3	90
3	0	7	73	20	290
4	0	~0	16	84	389
					769

PREFIGURANCE TABLES

RAINCAT 1

SEASON = 3

PRIORS EQUAL

	1	2	3	4	N
1	100	0	0	0	8
2	2	82	15	2	168
3	0	31	52	17	448
4	0	4	27	69	706
					1330

PRIORS PROPORTIONAL

	1	2	3	4	N
1	100	0	0	0	8
2	1	71	24	3	168
3	0	19	58	23	448
4	0	1	23	76	706
					1330

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PREFIGURANCE TABLES

RAINCAT 1

SEASON = 4

PRIORS EQUAL

	1	2	3	4	N
1	76	9	13	3	150
2	38	27	28	6	761
3	15	11	55	19	728
4	2	2	21	75	179
					1818

PRIORS PROPORTIONAL

	1	2	3	4	N
1	21	40	39	0	150
2	7	41	51	1	761
3	1	16	79	3	728
4	0	3	51	46	179
					1818

PREFIGURANCE TABLES

RAINCAT 2

SEASON = 1

PRIORS EQUAL

	1	2	3	4	5	N
1	68	18	6	3	8	66
2	51	32	6	7	4	486
3	25	16	22	29	9	593
4	15	10	17	52	5	155
5	0	13	0	0	88	8

1308

PRIORS PROPORTIONAL

	1	2	3	4	5	N
1	0	85	14	2	0	66
2	0	83	16	1	0	486
3	0	37	59	3	0	593
4	0	26	61	13	0	155
5	0	25	50	0	25	8

1308

PREFIGURANCE TABLES

RAINCAT 2

SEASON = 2

PRIORS EQUAL

	1	2	3	4	5	N
1	0	0	0	0	0	0
2	0	76	22	2	0	90
3	0	41	40	16	2	290
4	0	3	17	61	19	371
5	0	0	0	6	94	18
						769

PRIORS PROPORTIONAL

	1	2	3	4	5	N
1	0	0	0	0	0	0
2	0	38	59	3	0	90
3	0	7	73	20	0	290
4	0	20	17	83	0	371
5	0	0	0	78	22	18
						769

PREFIGURANCE TABLES

RAINCAT 2

SEASON = 3

PRIORS EQUAL

	1	2	3	4	5	N
1	100	0	0	0	0	8
2	2	82	15	2	0	168
3	0	31	50	17	2	448
4	0	5	28	43	24	591
5	0	0	9	20	71	115
						1330

PRIORS PROPORTIONAL

	1	2	3	4	5	N
1	100	0	0	0	0	8
2	1	71	24	4	0	168
3	0	19	58	23	0	448
4	0	1	27	70	2	591
5	0	0	5	58	37	115
						1330

PREFIGURANCE TABLES

RAINCAT 2

SEASON = 4

PRIORS EQUAL

	1	2	3	4	5	N
1	76	9	11	4	0	150
2	38	27	28	6	0	761
3	15	11	53	17	4	728
4	2	2	22	46	28	165
5	0	0	0	7	93	14
						1818

PRIORS PROPORTIONAL

	1	2	3	4	5	N
1	21	40	39	0	0	150
2	7	41	52	1	0	761
3	1	16	79	3	0	728
4	0	3	56	40	1	165
5	0	0	29	57	14	14
						1818

PREFIGURANCE TABLES

RAINCAT 3

SEASON = 1

PRIORS EQUAL

	1	2	3	4	5	6	7	8	N
1	68	23	2	6	2	0	0	0	66
2	49	35	7	1	5	3	0	0	486
3	27	20	15	10	13	16	0	0	400
4	15	7	12	20	25	20	0	1	193
5	14	9	9	19	34	15	1	0	140
6	7	0	7	0	0	87	0	0	15
7	0	0	25	25	0	25	25	0	4
8	0	25	0	50	25	0	0	0	4
									1308

PRIORS PROPORTIONAL

	1	2	3	4	5	6	7	8	N
1	0	86	11	2	2	0	0	0	66
2	0	85	12	1	2	0	0	0	486
3	0	49	41	5	4	1	0	0	400
4	0	26	45	20	9	0	0	0	193
5	0	30	31	24	15	0	0	0	140
6	0	13	67	7	0	13	0	0	15
7	0	25	75	0	0	0	0	0	4
8	0	25	25	50	0	0	0	0	4
									1308

PREFIGURANCE TABLES

RAINCAT 3

SEASON = 2

PRIORS EQUAL

	1	2	3	4	5	6	7	8	N
1	0	0	0	0	0	0	0	0	0
2	0	70	18	12	0	0	0	0	90
3	0	43	39	14	3	1	1	0	191
4	0	16	22	36	12	8	5	0	99
5	0	4	5	29	26	22	14	0	286
6	0	0	2	12	16	44	26	0	85
7	0	0	0	0	0	6	94	0	16
8	0	0	0	0	0	0	100	0	2
									769

PRIORS PROPORTIONAL

	1	2	3	4	5	6	7	8	N
1	0	0	0	0	0	0	0	0	0
2	0	29	58	1	12	0	0	0	90
3	0	11	74	3	13	0	0	0	191
4	0	0	51	3	44	2	0	0	99
5	0	0	12	1	82	5	0	0	286
6	0	0	2	0	84	14	0	0	85
7	0	0	0	0	50	6	44	0	16
8	0	0	0	0	100	0	0	0	2
									769

PREFIGURANCE TABLES

RAINCAT 3

SEASON = 3

PRIORS EQUAL

	1	2	3	4	5	6	7	8	N
1	100	0	0	0	0	0	0	0	8
2	2	77	13	6	1	1	0	0	168
3	0	42	27	20	8	2	≈0	≈0	250
4	0	12	23	44	113	5	3	2	198
5	0	7	8	33	17	18	9	7	413
6	0	0	2	19	15	34	10	22	178
7	0	0	2	18	8	15	23	35	66
8	0	0	0	0	4	16	4	76	49
									1330

PRIORS PROPORTIONAL

	1	2	3	4	5	6	7	8	N
1	100	0	0	0	0	0	0	0	8
2	1	74	17	1	7	0	0	0	168
3	0	33	40	6	21	1	0	0	250
4	0	8	31	15	45	0	2	0	198
5	0	3	16	4	70	6	≈0	≈0	413
6	0	0	3	1	65	24	1	7	178
7	0	0	0	0	50	17	11	23	66
8	0	0	0	0	25	20	4	51	49
									1330

PREFIGURANCE TABLES

RAINCAT 3

SEASON = 4

PRIORS EQUAL

	1	2	3	4	5	6	7	8	N
1	76	7	7	8	2	0	0	0	150
2	38	27	14	16	5	0	0	0	761
3	17	11	24	35	11	1	1	0	543
4	8	7	12	41	24	5	1	2	185
5	2	1	3	30	46	12	2	5	122
6	5	2	0	5	33	47	9	0	43
7	0	0	0	0	0	0	100	0	7
8	0	0	0	0	0	0	0	100	7
									1818

PRIORS PROPORTIONAL

	1	2	3	4	5	6	7	8	N
1	24	47	29	0	0	0	0	0	150
2	8	50	41	0	1	0	0	0	761
3	2	23	71	0	4	0	0	0	543
4	1	12	77	2	8	0	1	0	185
5	0	1	58	1	32	6	2	1	122
6	0	12	12	2	35	37	2	0	43
7	0	0	14	0	14	0	71	0	7
8	0	0	0	0	0	0	0	100	7
									1818

PREFIGURANCE TABLES

RAINCAT 4

SEASON = 1

PRIORS EQUAL

	1	2	3	4	5	6	7	8	N
1	27	51	12	3	0	5	0	1	74
2	18	58	8	2	1	10	0	3	564
3	18	34	8	1	4	26	1	9	524
4	19	20	3	5	5	34	?	13	262
5	6	27	7	4	10	31	3	12	195
6	6	12	0	6	0	59	12	6	17
7	0	0	0	0	0	0	100	0	4
8	0	20	0	0	0	20	0	60	5
									1645

PRIORS PROPORTIONAL

	1	2	3	4	5	6	7	8	N
1	0	82	14	3	1	0	0	0	74
2	0	81	16	2	1	0	0	0	564
3	0	56	35	6	2	0	≈0	0	524
4	0	42	37	16	3	0	≈0	0	262
5	0	38	38	17	6	0	0	0	195
6	0	35	47	18	0	0	0	0	17
7	0	0	25	0	0	0	75	0	4
8	0	20	0	60	20	0	0	0	5
									1645

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PREFIGURANCE TABLES

RAINCAT 4

SEASON = 2

PRIORS EQUAL

	1	2	3	4	5	6	7	8	N
1	0	0	0	0	0	0	0	0	0
2	0	67	21	12	0	0	0	0	95
3	0	37	37	23	3	0	0	0	231
4	0	8	30	38	7	11	6	0	142
5	0	5	10	29	15	25	16	0	344
6	0	1	3	14	15	31	36	0	98
7	0	0	0	0	0	19	81	0	16
8	0	0	0	0	0	0	100	0	2
									928

PRIORS PROPORTIONAL

	1	2	3	4	5	6	7	8	N
1	0	0	0	0	0	0	0	0	0
2	0	21	67	0	12	0	0	0	95
3	0	8	70	0	23	0	0	0	231
4	0	0	46	0	54	1	0	0	142
5	0	0	20	0	77	3	0	0	344
6	0	0	4	0	91	5	0	0	98
7	0	0	0	0	94	6	0	0	16
8	0	0	0	0	100	0	0	0	2
									928

PREFIGURANCE TABLES

RAINCAT 4

SEASON = 3

PRIORS EQUAL

	1	2	3	4	5	6	7	8	N
1	100	0	0	0	0	0	0	0	8
2	33	48	12	5	0	2	0	0	172
3	15	30	24	23	4	4	0	0	274
4	8	19	21	29	9	6	6	1	233
5	3	10	11	26	13	17	12	8	551
6	0	2	4	18	13	22	11	29	233
7	0	1	5	20	16	10	22	26	107
8	0	0	0	4	4	14	8	71	51
									1629

PRIORS PROPORTIONAL

	1	2	3	4	5	6	7	8	N
1	0	88	13	0	0	0	0	0	8
2	0	73	20	3	5	0	0	0	172
3	0	35	24	4	36	1	0	0	274
4	0	19	21	2	57	0	1	0	233
5	0	8	12	2	70	6	1	0	551
6	0	1	3	2	67	22	3	2	233
7	0	0	3	0	65	18	10	4	107
8	0	0	0	0	29	35	14	22	51
									1629

PREFIGURANCE TABLES

RAINCAT 4

SEASON = 4

PRIORS EQUAL

	1	2	3	4	5	6	7	8	N
1	69	10	6	11	1	1	0	2	158
2	38	24	15	17	3	0	0	2	845
3	20	9	22	34	7	1	1	5	601
4	15	1	14	38	18	2	3	9	218
5	1	1	4	32	22	2	12	26	157
6	2	9	0	5	22	20	24	18	55
7	0	0	0	0	11	0	89	0	9
8	0	0	0	0	0	0	0	100	9
									2052

PRIORS PROPORTIONAL

	1	2	3	4	5	6	7	8	N
1	8	75	15	0	2	0	0	0	158
2	3	65	30	0	2	0	0	0	845
3	1	35	60	0	4	0	0	0	601
4	0	20	70	0	11	0	0	0	218
5	0	2	58	0	36	3	1	0	157
6	0	13	24	0	48	16	0	0	55
7	0	0	11	0	78	0	11	0	9
8	0	0	56	0	44	0	0	0	9
									2052

PREFIGURANCE TABLES

RAINCAT 5

SEASON = 1

PRIORS EQUAL

	1	2	3	4	5	6	7	8	N
1	73	17	3	3	1	3	0	0	70
2	49	29	7	1	7	7	0	1	498
3	27	14	11	8	15	23	≈0	1	419
4	18	11	11	16	17	25	≈0	1	207
5	13	13	10	19	22	21	1	1	144
6	7	7	0	0	0	87	0	0	15
7	0	0	0	0	0	0	100	0	4
8	0	0	0	0	0	0	0	100	5
									1362

PRIORS PROPORTIONAL

	1	2	3	4	5	6	7	8	N
1	0	87	10	1	1	0	0	0	70
2	0	84	13	2	2	0	0	0	498
3	0	52	40	4	4	≈0	0	0	419
4	0	38	43	16	4	0	0	0	207
5	0	31	42	13	14	0	0	0	144
6	0	13	60	13	0	13	0	0	15
7	0	50	25	0	0	0	25	0	4
8	0	20	20	0	0	0	0	60	5
									1362

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PREFIGURANCE TABLES

RAINCAT 5

SEASON = 2

PRIORS EQUAL

	1	2	3	4	5	6	7	8	N
1	0	0	0	0	0	0	0	0	0
2	0	62	20	12	4	0	1	0	90
3	0	44	38	13	4	0	2	0	191
4	0	15	22	30	14	12	6	0	99
5	0	4	9	32	14	27	14	0	286
6	0	0	2	18	13	43	25	0	85
7	0	0	0	6	6	6	81	0	16
8	0	0	0	50	0	0	50	0	2
									769

PRIORS PROPORTIONAL

	1	2	3	4	5	6	7	8	N
1	0	0	0	0	0	0	0	0	0
2	0	10	73	0	17	0	0	0	90
3	0	5	76	0	18	0	0	0	191
4	0	0	42	2	55	1	0	0	99
5	0	1	13	0	81	4	1	0	286
6	0	0	2	0	87	10	1	0	85
7	0	0	0	0	75	0	25	0	16
8	0	0	0	0	100	0	0	0	2
									769

PREFIGURANCE TABLES

RAINCAT 5

SEASON = 3

PRIORS EQUAL

	1	2	3	4	5	6	7	8	N
1	100	0	0	0	0	0	0	0	8
2	6	77	8	7	1	2	0	0	168
3	1	45	22	21	6	3	3	0	257
4	0	15	17	47	9	4	5	3	208
5	0	5	9	38	13	14	11	9	423
6	0	0	1	24	12	24	15	24	178
7	0	0	0	23	9	11	26	32	66
8	0	0	0	0	2	16	10	71	49

1357

PRIORS PROPORTIONAL

	1	2	3	4	5	6	7	8	N
1	50	50	0	0	0	0	0	0	8
2	1	77	14	10	8	0	0	0	168
3	0	39	34	3	23	1	0	0	257
4	0	10	27	11	51	0	0	0	208
5	0	3	14	4	72	6	0	1	423
6	0	0	2	1	72	21	1	3	178
7	0	0	2	0	51	17	3	18	66
8	0	0	0	0	45	16	0	39	49

1357

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PREFIGURANCE TABLES

RAINCAT 5

SEASON = 4

PRIORS EQUAL

	1	2	3	4	5	6	7	8	N
1	77	9	3	7	3	0	0	0	150
2	44	25	12	13	3	1	0	1	798
3	24	11	22	28	10	1	1	3	565
4	13	7	10	43	15	3	3	6	193
5	5	1	1	28	38	5	11	10	135
6	0	9	0	5	25	45	9	7	44
7	0	0	0	0	14	0	86	0	7
8	0	0	0	0	0	0	0	100	7
									1899

PRIORS PROPORTIONAL

	1	2	3	4	5	6	7	8	N
1	21	51	29	0	0	0	0	0	150
2	10	51	39	0	1	0	0	0	798
3	3	25	68	0	4	0	0	0	565
4	2	18	72	1	8	1	0	0	193
5	0	5	57	0	32	4	1	1	135
6	0	14	16	0	50	20	0	0	44
7	0	0	14	0	20	14	43	0	7
8	0	0	57	0	14	0	0	29	7
									1899

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APPENDIX D
POSTAGREEMENT TABLES*

*Relative frequency of classification in each category, given the category into which observations were classified. If the actual category is a and the classified category is c , these tables give approximations of the conditional probabilities, $P(a|c)$. Postagreement, for any category, is the entry on the diagonal.

POSTAGREEMENT TABLES

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APICAT

AV = 0 EQUAL PRIORS				
OBS CAT	% CLASSIFIED IN CAT			
	1	2	3	
1	76	39	14	
2	23	45	46	
3	1	16	40	
N	1265	443	457	2165

APICAT

AV = 1 EQUAL PRIORS				
OBS CAT	% CLASSIFIED IN CAT			
	1	2	3	
1	75	39	14	
2	23	45	47	
3	2	16	38	
N	1342	420	466	2228

APICAT

AV = 0 PROPORATIONAL PRIORS				
OBS CAT	% CLASSIFIED IN CAT			
	1	2	3	
1	70	24	7	
2	26	51	35	
3	4	25	58	
N	1535	471	159	2165

APICAT

AV = 1 PROPORTIONAL PRIORS				
OBS CAT	% CLASSIFIED IN CAT			
	1	2	3	
1	70	25	8	
2	26	49	38	
3	4	26	54	
N	1589	480	159	2228

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POSTAGREEMENT TABLES

RAINCAT 1

SEASON = 1

PRIORS EQUAL

	1	2	3	4
1	10	5	2	1
2	53	56	15	10
3	32	33	69	61
4	5	6	15	29
N	464	307	233	304

PRIORS PROPORTIONAL

	1	2	3	4
1	0	8	2	2
2	0	56	14	12
3	0	30	65	47
4	0	6	19	39
N	0	720	537	51
RF	5	37	45	12

POSTAGREEMENT TABLES

RAINCAT 1

SEASON = 2

PRIORS EQUAL

	1	2	3	4
1	0	0	0	0
2	0	34	10	1
3	0	60	58	15
4	0	6	32	85
N	0	200	201	368

PRIORS PROPORTIONAL

	1	2	3	4
1	0	0	0	0
2	0	61	16	1
3	0	38	65	15
4	0	2	19	84
N	0	56	325	388
RF	0	12	38	51

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POSTAGREEMENT TABLES

RAINCAT 1

SEASON = 3

PRIORS EQUAL

	1	2	3	4
1	73	0	0	0
2	27	45	6	1
3	0	46	51	14
4	0	9	43	86
N	11	306	449	564

PRIORS PROPORTIONAL

	1	2	3	4
1	80	0	0	0
2	20	57	9	1
3	0	40	56	16
4	0	2	35	83
N	10	209	463	648
RF	1	13	34	53

POSTAGREEMENT TABLES

RAINCAT 1

SEASON = 4

PRIORS EQUAL

	1	2	3	4
1	22	4	3	1
2	56	69	32	14
3	21	26	59	44
4	1	10	6	41
N	520	302	672	324

PRIORS PROPORTIONAL

	1	2	3	4
1	34	12	5	0
2	57	63	35	5
3	9	24	52	22
4	0	1	8	73
N	95	495	1114	114
RF	8	42	40	10

POSTAGREEMENT TABLES

RAINCAT 2

SEASON = 1

PRIORS EQUAL

Classified in Category

	1	2	3	4	5
1	10	4	2	1	3
2	53	56	16	11	23
3	32	34	68	60	57
4	5	6	14	28	9
5	0	~0	0	0	8
N	461	281	191	285	90

PRIORS PROPORTIONAL

	1	2	3	4	5
1	0	8	2	2	0
2	0	56	14	15	0
3	0	30	66	42	50
4	0	6	18	42	0
5	0	~0	1	0	50
N	0	720	536	48	4
RF*	5	37	45	12	1

*Relative Frequency of observations from each category.

POSTAGREEMENT TABLES

RAINCAT 2

SEASON = 2

PRIORS EQUAL

Classified in Category

	1	2	3	4	5
1	0	0	0	0	0
2	0	34	10	1	0
3	0	60	59	17	6
4	0	6	31	82	75
5	0	0	0	0	18
N	0	200	199	277	93

PRIORS PROPORTIONAL

	1	2	3	4	5
1	0	0	0	0	0
2	0	61	16	1	0
3	0	38	65	15	0
4	0	2	19	80	0
5	0	0	0	4	100
N	0	56	327	382	4
RF	0	12	38	48	2

POSTAGREEMENT TABLES

RAINCAT 2

SEASON = 3

PRIORS EQUAL

	1	2	3	4	5
1	73	0	0	0	0
2	27	45	6	1	0
3	0	46	53	22	3
4	0	9	39	71	62
5	0	0	2	6	35
N	11	306	422	358	233

PRIORS PROPORTIONAL

	1	2	3	4	5
1	80	0	0	0	0
2	20	57	9	1	0
3	0	40	56	18	3
4	0	2	34	70	24
5	0	0	1	11	72
N	10	209	466	587	58
RF	1	13	34	44	9

POSTAGREEMENT TABLES

RAINCAT 2

SEASON = 4

PRIORS EQUAL

	1	2	3	4	5
1	22	4	3	2	0
2	56	69	33	18	3
3	21	26	59	49	30
4	1	1	6	30	52
5	0	0	0	~0	15
N	520	300	652	257	89

PRIORS PROPORTIONAL

	1	2	3	4	5
1	34	12	5	0	0
2	57	63	35	5	0
3	9	24	51	24	0
4	0	1	8	63	50
5	0	0	~0	8	50
N	95	495	1121	103	4
RF	8	42	40	9	1

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POSTAGREEMENT TABLES

RAINCAT 3

SEASON = 1

PRIORS EQUAL

	1	2	3	4	5	6	7	8
1	10	5	1	3	1	0	0	0
2	55	58	27	3	14	9	0	0
3	24	27	43	35	30	43	0	0
4	6	4	18	34	28	25	0	100
5	4	4	10	23	27	14	50	0
6	0	0	1	0	0	9	0	0
7	0	0	1	1	0	1	50	0
8	0	0	0	2	1	0	2	0
N	438	291	134	115	175	151	2	2

PRIORS PROPORTIONAL

	1	2	3	4	5	6	7	8
1	0	7	2	1	2	0	0	0
2	0	54	15	5	17	0	0	0
3	0	26	44	20	23	60	0	0
4	0	7	23	38	27	0	0	0
5	0	6	12	33	32	0	0	0
6	0	0	3	1	0	40	0	0
7	0	0	1	0	0	0	0	0
8	0	0	0	2	0	0	0	0
N	0	763	374	100	66	5	0	0
RF	5	37	31	15	11	1	0	0

POSTAGREEMENT TABLES

RAINCAT 3

SEASON = 2

PRIORS EQUAL

	1	2	3	4	5	6	7	8
1	0	0	0	0	0	0	0	0
2	0	37	12	7	0	0	0	0
3	0	48	58	17	5	1	2	0
4	0	9	17	22	11	7	6	0
5	0	6	11	50	70	57	47	0
6	0	0	2	6	13	34	25	0
7	0	0	0	0	0	1	17	0
8	0	0	0	0	0	0	2	0
N	0	172	129	166	105	110	87	0

PRIORS PROPORTIONAL

	1	2	3	4	5	6	7	8
1	0	0	0	0	0	0	0	0
2	0	54	19	8	3	0	0	0
3	0	44	51	42	6	0	0	0
4	0	0	18	25	11	7	0	0
5	0	2	12	25	59	50	0	0
6	0	0	1	0	18	40	0	0
7	0	0	0	0	2	3	100	0
8	0	0	0	0	1	0	0	0
N	0	48	278	12	394	30	7	0
RF	0	12	25	13	37	11	2	0

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POSTAGREEMENT TABLES

RAINCAT 3

SEASON = 3

PRIORS EQUAL

	1	2	3	4	5	6	7	8
1	73	0	0	0	0	0	0	0
2	27	46	13	3	1	1	0	0
3	0	37	39	15	14	4	1	1
4	0	8	26	26	17	5	6	2
5	0	10	19	42	46	44	49	23
6	0	0	2	10	17	36	23	28
7	0	0	1	4	3	6	19	18
8	0	0	0	0	1	5	2	28
N	11	284	175	329	151	170	80	130

PRIORS PROPORTIONAL

	1	2	3	4	5	6	7	8
1	80	0	0	0	0	0	0	0
2	20	53	11	3	2	0	0	0
3	0	35	38	22	9	2	0	0
4	0	6	24	46	15	0	20	0
5	0	5	25	28	48	29	13	4
6	0	0	2	2	19	46	7	24
7	0	0	0	0	5	12	47	27
8	0	0	0	0	2	11	13	45
N	10	232	259	65	603	91	15	55
RF	1	13	19	15	31	13	5	4

POSTAGREEMENT TABLES

RAINCAT 3

SEASON = 4

PRIORS EQUAL

	1	2	3	4	5	6	7	8
1	22	4	4	3	1	0	0	0
2	56	71	39	28	18	6	5	0
3	18	20	47	43	28	13	24	11
4	3	5	8	17	20	19	5	17
5	≈0	≈0	1	8	26	26	14	33
6	≈0	≈0	0	≈0	6	37	19	0
7	0	0	0	0	0	0	33	0
8	0	0	0	0	0	0	0	0
N	513	286	275	435	216	54	21	18

PRIORS PROPORTIONAL

	1	2	3	4	5	6	7	8
1	34	12	4	0	0	0	0	0
2	55	63	33	0	11	0	0	0
3	10	21	40	0	19	0	10	0
4	1	4	15	60	15	0	10	0
5	0	≈0	7	20	39	30	20	13
6	0	1	1	20	15	70	10	0
7	0	0	≈0	0	1	0	50	0
8	0	0	0	0	0	0	0	87
N	106	600	966	5	100	23	10	8
RF	8	42	30	10	7	2	≈0	≈0

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POSTAGREEMENT TABLES

SEASON = 1

RAINCAT 4

PRIORS EQUAL

	1	2	3	4	5	6	7	8
1	7	6	8	5	0	1	0	1
2	37	50	39	28	12	15	0	13
3	33	27	34	13	36	39	19	37
4	18	8	7	31	20	25	24	27
5	4	8	12	21	32	17	29	19
6	~0	~0	0	3	0	3	10	1
7	0	0	0	0	0	0	19	0
8	0	~0	0	0	0	~0	0	2
N	277	651	116	39	59	356	21	126

PRIORS PROPORTIONAL

	1	2	3	4	5	6	7	8
1	0	6	2	2	2	0	0	0
2	0	45	20	8	20	0	0	0
3	0	29	39	25	27	0	33	0
4	0	11	21	34	22	0	17	0
5	0	7	16	27	27	0	0	0
6	0	1	2	2	0	0	0	0
7	0	0	~0	0	0	0	50	0
8	0	~0	0	2	2	0	0	0
N	0	1004	468	126	41	0	6	0
RF	5	34	32	16	12	1	~0	~0

POSTAGREEMENT TABLES

RAINCAT 4

SEASON = 2

PRIORS EQUAL

	1	2	3	4	5	6	7	8
1	0	0	0	0	0	0	0	0
2	0	36	11	5	0	0	0	0
3	0	48	46	23	8	0	1	0
4	0	6	23	23	12	11	8	0
5	0	9	19	43	62	64	48	0
6	0	1	2	6	18	23	30	0
7	0	0	0	0	0	2	11	0
8	0	0	0	0	0	0	2	0
N	0	177	186	231	85	133	116	0

PRIORS PROPORTIONAL

	1	2	3	4	5	6	7	8
1	0	0	0	0	0	0	0	0
2	0	51	18	0	2	0	0	0
3	0	46	44	0	10	0	0	0
4	0	0	18	0	15	6	0	0
5	0	3	19	0	52	56	0	0
6	0	0	1	02	17	31	0	0
7	0	0	0	0	3	6	50	0
8	0	0	0	0	0	0	0	0
N	0	39	363	0	510	16	0	0
RF	0	10	25	15	37	11	2	0

POSTAGREEMENT TABLES

RAINCAT 4

SEASON = 3

PRIORS EQUAL

	1	2	3	4	5	6	7	8
1	6	0	0	0	0	0	0	0
2	40	30	10	2	0	2	0	0
3	28	30	31	18	7	6	1	1
4	13	16	23	20	14	8	10	2
5	12	21	29	41	47	48	50	24
6	1	1	5	12	20	27	19	38
7	0	0	2	6	11	6	18	16
8	0	0	0	1	1	4	3	20
N	142	273	212	347	148	192	137	178

PRIORS PROPORTIONAL

	1	2	3	4	5	6	7	8
1	0	2	0	0	0	0	0	0
2	0	39	15	14	1	0	0	0
3	0	30	29	28	11	2	0	0
4	0	14	22	11	15	1	6	0
5	0	14	29	36	45	25	21	9
6	0	1	4	11	18	41	21	23
7	0	0	1	0	8	15	32	18
8	0	0	0	0	2	15	21	50
N	0	322	225	36	867	123	34	22
RF	0	11	17	14	34	14	7	3

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POSTAGREEMENT TABLES

RAINCAT 4

SEASON = 4

PRIORS EQUAL

	1	2	3	4	5	6	7	8
1	19	6	3	3	1	3	0	2
2	55	72	41	29	16	14	7	12
3	21	19	43	41	27	17	14	23
4	5	1	10	16	25	17	12	16
5	≈0	≈0	2	10	22	10	32	32
6	≈0	2	0	1	8	38	22	8
7	0	0	0	0	1	0	14	0
8	0	0	0	0	0	0	0	7
N	588	278	311	506	153	29	59	128

PRIORS PROPORTIONAL

	1	2	3	4	5	6	7	8
1	32	13	3	0	2	0	0	0
2	56	59	28	0	10	0	0	0
3	12	22	40	0	16	0	25	0
4	0	5	17	0	14	0	0	0
5	0	≈0	10	0	35	31	50	0
6	0	1	1	0	16	69	0	0
7	0	0	≈0	0	4	0	25	0
8	0	0	1	0	2	0	0	0
N	41	930	901	0	163	13	4	0
RF	8	41	29	11	8	3	≈0	≈0

POSTAGREEMENT TABLES

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RAINCAT 5

SEASON = 1

PRIORS EQUAL

	1	2	3	4	5	6	7	8
1	11	5	2	2	1	1	0	0
2	52	55	29	5	22	15	0	24
3	25	23	39	33	37	43	25	18
4	8	9	19	33	21	22	13	18
5	4	7	12	26	19	13	13	12
6	≈0	≈0	0	0	0	6	0	0
7	0	0	0	0	0	0	50	0
8	0	0	0	0	0	0	0	29
N	466	256	119	102	165	229	8	17

PRIORS PROPORTIONAL

	1	2	3	4	5	6	7	8
1	0	7	2	1	2	0	0	0
2	0	51	16	10	18	0	0	0
3	0	27	42	19	29	33	0	0
4	0	9	22	42	15	0	0	0
5	0	5	15	24	36	0	0	0
6	0	≈0	2	3	0	67	0	0
7	0	≈0	≈0	0	0	0	100	0
8	0	≈0	≈0	0	0	0	0	100
N	0	822	400	78	55	3	1	3
RF	5	37	31	15	11	1	≈0	≈0

POSTAGREEMENT TABLES

RAINCAT 5

SEASON = 2

PRIORS EQUAL

	1	2	3	4	5	6	7	8
1	0	0	0	0	0	0	0	0
2	0	34	13	6	5	0	1	0
3	0	50	52	14	10	0	5	0
4	0	9	16	17	18	9	7	0
5	0	7	18	52	52	61	47	0
6	0	0	1	9	14	28	24	0
7	0	0	0	1	1	1	15	0
8	0	0	0	1	0	0	1	0
N	0	165	139	172	79	127	87	0

PRIORS PROPORTIONAL

	1	2	3	4	5	6	7	8
1	0	0	0	0	0	0	0	0
2	0	43	22	0	4	0	0	0
3	0	48	50	0	8	0	0	0
4	0	0	14	100	13	5	0	0
5	0	10	13	0	55	55	29	0
6	0	0	1	0	17	40	14	0
7	0	0	0	0	3	0	57	0
8	0	0	0	0	0	0	0	0
N	0	21	294	2	425	20	7	0
RF	0	12	25	13	37	11	2	0

POSTAGREEMENT TABLES

RAINCAT 5

SEASON = 4

PRIORS EQUAL

	1	2	3	4	5	6	7	8
1	18	5	2	3	2	0	0	0
2	55	68	39	26	14	21	3	15
3	21	21	50	40	32	15	14	27
4	4	5	8	21	16	12	16	18
5	1	≈0	1	10	29	13	41	23
6	0	1	0	1	6	38	11	5
7	0	0	0	0	1	0	16	0
8	0	0	0	0	0	0	0	12
N	639	296	244	397	174	52	37	60

PRIORS PROPORTIONAL

	1	2	3	4	5	6	7	8
1	24	11	4	0	0	0	0	0
2	59	60	32	67	4	0	0	25
3	13	21	40	0	19	0	0	0
4	3	5	14	33	14	6	0	0
5	0	1	8	0	40	35	25	25
6	0	1	1	0	20	53	0	0
7	0	0	≈0	0	2	6	75	0
8	0	0	≈0	0	1	0	0	50
N	128	668	967	3	108	17	4	4
RF	8	42	30	10	7	2	≈0	≈0